The Macroeconomic Effects of Supply Chain Shocks: Evidence from Global Shipping Disruptions *

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Abstract

This paper studies the macroeconomic consequences of global supply chain disruptions, focusing on maritime choke points critical to international trade. We identify supply chain shocks using narrative accounts and high-frequency financial data on disruptions at key locations such as the Suez and Panama Canal. These shocks lead to a persistent increase in shipping costs, causing declines in economic activity and sustained increases in producer and consumer prices. Shipping capacity initially contracts before adjusting sluggishly. The shocks also increase delivery times and industry shortages but are unrelated to geopolitical risk, consistent with exogenous disruptions. Using granular input-output data, we document heterogeneous sectoral effects and estimate substitution elasticities, finding limited short-run but stronger medium-run substitution.

JEL classification: E30, E31, F60, R40

Keywords: Supply chain, disruptions, shipping costs, macroeconomic effects

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1. Introduction

Over the last decades, supply chains have become increasingly interconnected. Recent events such as the Covid pandemic, Russia's invasion of Ukraine, and extreme weather have all highlighted the fragility of global supply chains. Such disruptions pose significant risks to the global economy, as they can have profound macroeconomic consequences, affecting output, inflation and employment across countries. Better understanding of the macroeconomic impacts of supply chain disruptions is crucial to inform policy responses aimed at building more resilient and adaptable supply chains in an increasingly uncertain global environment.

In this paper, we provide new evidence on the macroeconomic implications of supply chain disruptions. Our identification strategy leverages the fact that global supply chains critically rely on maritime trade, which in turn is heavily dependent on a small number of strategic choke points. The most important choke points are the Suez Canal and the Panama Canal. We perform a comprehensive narrative account of disruptive incidents at these choke points, such as groundings, collisions or extreme weather events. These events can cause major disruptions to the global shipping network and are plausibly exogenous to the global economy. In a next step, we isolate the market impact of the shipping disruption by the change in shipping rates in a narrow window around the event, exploiting high-frequency financial data. To address remaining concerns about predictability, we orthogonalize the surprises with respect to macroeconomic and financial data pre-dating the disruptive events. Using the resulting series as an instrument in a VAR model of the global economy, we identify a structural supply chain shock.

An adverse supply chain shock causes a strong, persistent increase in shipping rates, with effects that extend well beyond the initial disruption. Even short-lived disruptions can trigger ripple effects lasting for months, as ship rerouting reduces effective capacity, creates bottlenecks, and disrupts the structure of the global shipping network. The increase in shipping cost passes-through commodity prices, which increase significantly with some lag. Global shipping capacity initially contracts before expanding sluggishly in response to persistently elevated shipping costs. Importantly, the shock does not lead to any significant changes in geopolitical risk. This is desired as we purposefully abstract from disruptive events related to geopolitical tensions as they may affect the global economy through channels unrelated to supply chains.

Global supply chain shocks also have meaningful effects on the U.S. economy. Industrial production falls significantly and persistently and U.S. consumer prices increase persistently. These stagflationary effects create a trade-off for monetary policy, reflected

in the ambiguous response of the short-term interest rate. Finally, the shock leads to a significant depreciation of the dollar.

Quantitatively, a shock increasing shipping rates by 10 percent leads to an increase in commodity prices by about 2 percent, an increase in the global shipping capacity by 0.3 percent, a fall in U.S. industrial production falls by around 0.5 percent and a rise in the U.S CPI increases by 0.2 percent.

We also show that the shock leads to a significant increase in supplier delivery times and an uptick in industry shortages—corroborating the interpretation of a supply chain shock. The sluggish increase in commodity prices together with the delayed increase in the shipping capacity also suggests that we are not merely picking up commodity price shocks.

A comprehensive series of sensitivity checks suggests that the results are robust along a number of dimensions, including the model specification, the sample period and the identification strategy. Specifically, the results are robust to relaxing the invertibility requirement or estimating the dynamic responses based on local projections.

Equipped with our identified supply chain shocks, we investigate the role of supply chain pressures in the recent inflationary episode. We find that supply chain shocks contribute meaningfully to the variation in inflation over the 2020–2022 period: they explain a considerable share of the rise in inflation through 2021, consistent with the timing of widespread logistical bottlenecks and maritime stress. However, they fail to account for the full extent of the inflation surge—suggesting that other factors such as fiscal stimulus, accommodative monetary policy and energy price shocks played an important role as well.

Counterfactual analyses suggest that monetary policy plays an important role in the transmission of supply chain shocks. A more aggressive monetary response could stabilize prices in the face of supply chain shocks, however, this comes at a cost of a significantly steeper fall in output.

Moving beyond aggregate impacts, we document substantial heterogeneity in the transmission of supply chain shocks across sectors. Using disaggregated data on industrial production and producer prices, we show that the effects vary systematically with sectors' exposure to intermediate inputs and global supply chains. Price pressures are particularly strong in upstream industries such as petroleum and metals, while output contractions are concentrated in downstream sectors, most notably motor vehicles, and in input-intensive non-durable industries such as chemicals and plastics. Motivated by these patterns, we estimate elasticities of substitution across intermediate inputs using granular input-output data. We find that substitution is close to zero in the short run,

rises to around one after one year, and peaks at about 1.5 after two years, pointing to sluggish but economically meaningful reallocation of sourcing across suppliers.

Related literature and contribution. This project contributes to a burgeoning literature studying the economic impacts of supply chain disruptions from both empirical and theoretical angles. Recent years have seen unprecedented strain on global supply chains—exacerbated by climate change and extreme weather—making it essential to understand how to enhance their resilience and adaptability.

A recent empirical literature studies the effects of supply chain pressures and shipping costs on the macroeconomy (Bini, 2025; Carrière-Swallow et al., 2023; Herriford et al., 2016; Jacks and Stuermer, 2021, among others). A number of studies have also constructed indices to directly measure supply chain pressures, using real-time congestion of containerships in major ports (Bai et al., 2024) or using purchasing managers index and transportation costs (Benigno et al., 2022), to assess how supply chain shocks affect economic outcomes. Caldara, Iacoviello, and Yu (2024) construct a newspaper based measure of input shortages and find that such shortages are associated with persistent inflationary effects. Fernández-Villaverde, Mineyama, and Song (2024) study the effects of geopolitical fragmentation and find the strongest effects in sectors that are closely linked to global markets. At a more disaggregated level, Blaum, Esposito, and Heise (2023) construct a measure of supply chain risk at the firm level based on transaction data on U.S. manufacturing imports, and show that shipping delays are associated with lower firm-level employment and revenue. Castro-Vincenzi et al. (2024) study how firms structure supply chains under climate risk. We contribute to this literature by providing new evidence pointing to considerable macroeconomic effects of supply chain disruptions.

Methodologically, our approach builds on the literature on high-frequency identification, which was developed in the monetary policy setting (Gertler and Karadi, 2015; Gürkaynak, Sack, and Swanson, 2005; Kuttner, 2001; Nakamura and Steinsson, 2018, among others) and more recently employed in the context of oil and carbon markets (Känzig, 2021; 2023). In this literature, policy surprises are identified using high-frequency asset price movements around policy events, such as FOMC or OPEC meetings. The idea is to isolate the impact of policy news by measuring the change in asset prices in a tight window around the events. We employ this approach in the context of global supply chains, allowing for credible identification under relatively weak structural assumptions.

On the theoretical side, we contribute to an influential theoretical literature that studies how supply chain disruptions propagate through production networks and can have

large aggregate impacts (Acemoglu, Akcigit, and Kerr, 2016; Acemoglu and Tahbaz-Salehi, 2024; Alessandria et al., 2023; Baqaee and Farhi, 2019; Carvalho and Tahbaz-Salehi, 2019; Comin, Johnson, and Jones, 2023, among others). To date, there is limited evidence on the substitution possibilities across firms and sectors. Prominent estimates include Atalay (2017) for the inner-nest elasticities of different materials, and Oberfield and Raval (2021) and Carvalho et al. (2021) for the outer-nest elasticities of materials, capital and labor. Most of the networks literature focuses on static settings, taking a longer term perspective. There are some exceptions, such as Afrouzi and Bhattarai (2023); La'O and Tahbaz-Salehi (2022); Rubbo (2023), and Minton and Wheaton (2023), however these papers focus on inflation and monetary policy. There is little work that aims to estimate long-term substitution possibilities across firms and sectors. We provide new reduced-form estimates of substitution elasticities across production factors, which can be used to discipline quantitative network models.

Outline. The paper proceeds as follows. Section 2 introduces our strategy to identify supply chain shocks. We discuss the role of choke points in global supply chains, provide a detailed narrative account of disruptions at these choke points, and construct a series of shipping cost surprises based on high-frequency data on shipping rates. In Section 3, we introduce our empirical framework. Section 4 presents our empirical results. In Section 5, we document sectoral heterogeneity in the effects of supply chain shocks and estimate elasticities of substitution across intermediate inputs using granular data. Section 6 concludes.

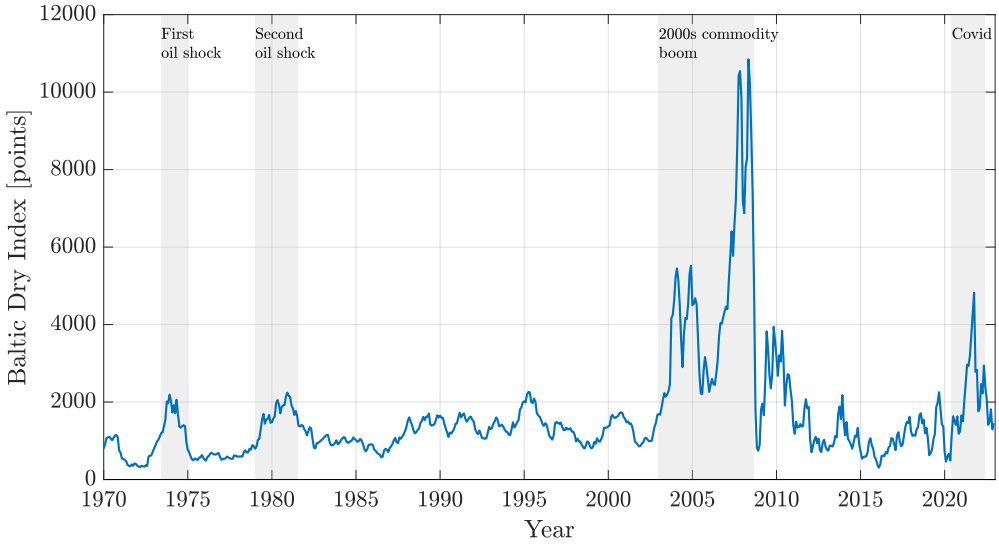
2. Identification Strategy

Global supply chains are heavily reliant on maritime trade, with over 80 percent of the world's trade by volume transported by sea. As a consequence, shipping rates offer a timely barometer of supply chain conditions.

Figure 1 shows the evolution of shipping rates, as proxied by the Baltic Dry Index (BDI), from the 1970s to date. The BDI tracks the cost of transporting bulk commodities like iron ore, coal, and grain across major shipping routes and is commonly used as a proxy for global shipping rates.

Fluctuations in shipping rates are driven by changes in global demand and supply. The sharp spikes during the oil shocks of the 1970s were clearly driven by supply disruptions. The surge in the 2000s, by contrast, was largely driven by booming Chinese demand for commodities. The Covid-19 period saw a mix of both—disrupted logistics

Figure 1: Global Shipping Rates as a Barometer of Supply Chain Pressures



and a rapid rebound in global goods demand. The fact that shipping rates are affected by both demand and supply dynamics complicates the identification of supply chain shocks based on shipping price movements. Simply regressing economic variables of interest on shipping costs will in general lead to biased results.

We overcome this challenge by leveraging the reliance of global supply chains on critical choke points combined with high-frequency financial information to isolate some variation in shipping rates that is driven by supply chain disruptions and plausibly exogenous to the world economy.

2.1. Choke Points in Global Supply Chains

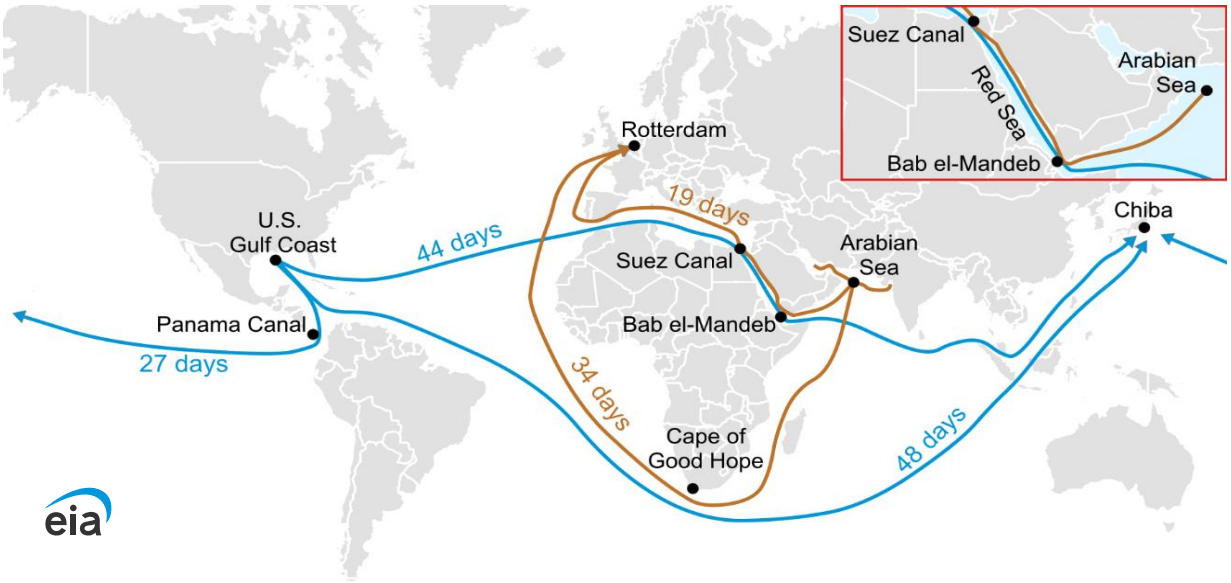
Maritime trade facilitates the movement of goods across vast distances at a relatively low cost and is crucial to the functioning of international commerce. Figure 2 displays the main global sea trade routes together with associated shipping times. A key feature of global shipping markets is the stark reliance on certain critical points, known as maritime choke points.

Maritime choke points are defined as narrow waterways that connect global sea trade routes. Such choke points are characterized by a narrow width, high share of global maritime trade, high shipping traffic, and few viable alternate routes. Disruptions at these choke points can have far-reaching consequences for global supply chains. The two most critical choke points are the Suez Canal and the Panama Canal, which we focus on in this paper. We start by providing some more background information on these two

choke points.

Suez Canal. The Suez Canal, located in Egypt, is a maritime choke point that connects the Mediterranean Sea and Red Sea through the Gulf of Suez. The Suez Canal provides the shortest sea trade route between Europe and Asia. For instance, vessels traveling through the Suez Canal for journeys between the Persian Gulf and Amsterdam-Rotterdam-Antwerp save 15 days of transit time in comparison to alternative routes (see Figure 2). Over 15 percent of international maritime trade passes through the Suez Canal, rendering international trade highly vulnerable to disruptions in the Suez Canal.

Figure 2: Major Global Sea Trade Routes, Choke Points, and Shipping Times



Notes: In Brown: Vessels traveling through the Suez Canal for journeys between the Persian Gulf and Amsterdam-Rotterdam-Antwerp save 15 days of transit time in comparison to alternative routes. In Blue: Vessels traveling through the Panama Canal for journeys between the U.S. Gulf Coast and Chiba, Japan save 17-21 days of transit time in comparison to alternative routes. Source: U.S. Energy Information Administration (2024).

Throughout its history, the Suez Canal has experienced numerous disruptions to shipping traffic due to its narrow, constrained passage—from vessel groundings and collisions to fires, piracy incidents, and adverse weather conditions (see Figure 3a). One such notable and recent incident occurred on March 23, 2021, when Ever Given, a container ship, ran aground and became lodged sideways across the canal for six days, blocking the trade route. While particularly significant, the Ever Given grounding is one of many disruptions that have affected this critical maritime choke point over the years. As an example, we provide below an excerpt of a Reuters news article discussing a grounding in the Suez Canal on November 8, 2004 (Reuters, 2004):

Egypt's Suez Canal has been blocked by a broken-down oil tanker and could stay shut for another two days (...)

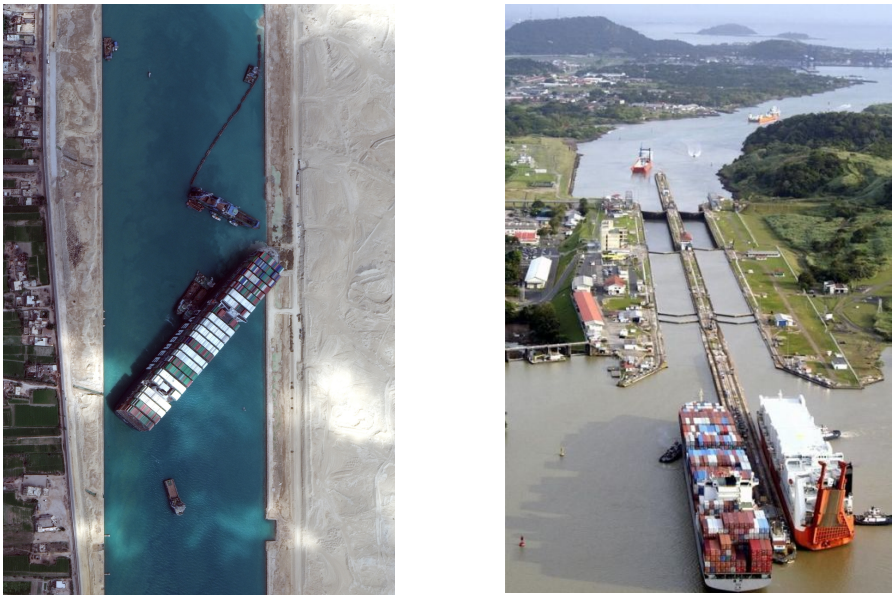
Navigation came to a standstill late on Saturday when the 154,000 deadweight-tonne Liberian-flagged vessel Tropic Brilliance, carrying a cargo of crude, ran aground while passing through the canal. (...)

Shipping sources expected traffic to be disrupted until Wednesday at least.

Shipping disruptions in the Suez Canal, such as the example above, are widely discussed across both mainstream and maritime-specific news agencies.

Figure 3: Maritime Choke Points

(a) Suez Canal (b) Panama Canal



Notes: Two of the world's most critical maritime choke points. Panel (a) shows the Ever Given container ship obstructing the Suez Canal during the March 2021 grounding, which disrupted global trade for nearly a week. Panel (b) shows vessels transiting the Panama Canal's lock system, which lifts and lowers ships through a freshwater channel, via Gatun Lake, to connect the Atlantic and Pacific Oceans.

Panama Canal. The Panama Canal, located in Panama, is a maritime choke point that connects the Atlantic Ocean and Pacific Ocean. The Panama Canal provides the shortest sea trade route between the oceans and accounts for around 46 percent of the trade between Northeast Asia and the U.S. East Coast. For instance, vessels traveling through the Panama Canal for journeys between the U.S. Gulf Coast and Chiba, Japan save 17-21 days of transit time in comparison to alternative routes (see Figure 2). Over 5 percent of international maritime trade passes through the Panama Canal.

Due to its narrow passage and reliance on freshwater for lock operations (see Figure 3b), the Panama Canal has experienced numerous disruptions to shipping traffic, from adverse weather conditions and fires to vessel groundings and collisions. Notably, in recent years, the shipping traffic through the Panama Canal has often been subject to transit and draft restrictions that limit the number and capacity of vessels, respectively, due to adverse weather conditions. As an example, we provide below an excerpt of a Reuters news article discussing a draft restriction in the Panama Canal on August 7, 2015 (2015):

> *The Panama Canal Authority will temporarily lower the maximum draft of ships passing through the canal, due to droughts caused by El Nino, authorities said on Friday.*
>
> *Starting on Sept. 8, the greatest draft allowed will be 39 feet (11.89 m), down from the current maximum of 39.5 feet (12.04 m), the Panama Canal Authority said.*
>
> *The change could affect about 20 percent of ships that use this route (...)*

Restrictions, as in the example above, are imposed by the Panama Canal Authority (ACP), the authority responsible for the administration, operation, and maintenance of the canal. When restrictions are imposed, the authority issues an "Advisory to Shipping" on their official website. Restrictions due to adverse weather conditions and other shipping disruptions are widely reported by both mainstream and maritime-specific news agencies.

2.2. A Narrative Analysis of Supply Chain Disruptions

We compile a comprehensive narrative account of events that disrupted shipping traffic through the Suez and the Panama Canal. For the Suez Canal, no official archive of disruptions exists. Therefore, we rely on leading newswires, searching for events that disrupted traffic in the canal, such as collisions, groundings, or storms. For the Panama Canal, we use official shipping advisories to identify draft restrictions but confirm the salience of these restrictions through contemporaneous newspaper reports.

Our dataset identifies 140 events that disrupted shipping traffic in the two canals between 1970 and 2022, including 95 events in the Suez Canal and 45 events in the Panama Canal. Table 1 provides an overview of the events in our dataset. The events in the Suez Canal include 58 vessel groundings, 8 vessel collisions, and 16 weather-related disruptions. The events in the Panama Canal include 39 weather-related disruptions, associated with El Nino events, landslides or floodings, as well as a few grounding and collisions.

Table 1: Disruptive Events at Maritime Choke Points

Panama Canal		Suez Canal	
Event Type	Number	Event Type	Number
Grounding	1	Grounding	58
Collision	1	Collision	8
Fire	1	Fire	5
El Nino/Rainfall	30	Weather	9
Landslide/Flooding	3	Sandstorm	7
Drought	6	Piracy/Rebels	2
Other	3	Other	6
Total	45	Total	95

In selecting events, we take great care to ensure that they are plausibly exogenous to the global economy. Specifically, we include vessel groundings, collisions, fires, piracy incidents, and adverse weather conditions that are plausibly exogenous to economic activity, while excluding events linked to geopolitical tensions in the Middle East. Some disruptions—such as weather-related restrictions—may be partially forecastable. In these cases, isolating the unanticipated component is crucial to avoid bias from anticipatory effects.

2.3. High-frequency Identification

The identified events vary in severity, and some may be at least partially anticipated. To gauge the importance of each event while accounting for potential anticipation effects, we adopt a high-frequency identification strategy that leverages financial market data on shipping rates.

The idea is the following. Disruptive events along global shipping routes are closely monitored by market experts and the reporting of these events can lead to significant market reactions. Thus, we can isolate the impact of a disruptive event by measuring the change in shipping rates in a tight window around the disruption. To the extent that the global economic outlook is priced at the time of the event and unlikely to change over the short event window, we isolate some unexpected variation in shipping rates that is plausibly exogenous. Doing this systematically across all our events, we construct a series of high-frequency shipping cost surprises, i.e. the unexpected component of shipping rates associated with a disruption in shipping markets. These surprises can be used to identify a structural supply chain shock.

Measuring shipping costs. We use the Baltic Dry Index (BDI), published daily by the London-based Baltic Exchange, to measure global shipping costs. The BDI is a composite of timecharter rates across three vessel classes—Capesize (40 percent), Panamax (30 percent), and Supramax (30 percent)—each of which reflects average shipping rates across a wide range of global dry bulk trade routes. As such, it provides a comprehensive measure of maritime transport costs for bulk commodities.

We focus on the BDI for two main reasons. First, it is a well-established barometer of global trade activity and is closely followed by market participants. Second, it is available at a daily frequency and spans a long historical sample period, making it well-suited for our time-series high-frequency identification approach.

A potential limitation is that the BDI covers only dry bulk shipping, excluding containerized freight. Data on container rates are only available at lower frequency and with more limited historical coverage. However, since freight rates tend to co-move across shipping segments due to shared cost drivers and capacity constraints, the BDI remains a broadly informative proxy for global shipping conditions.

Construction of shipping cost surprises. We construct a series of shipping cost surprises by measuring how shipping costs change around the disruptive events we identify. Specifically, we record the percentage change in the shipping costs on the event reporting day compared to the last trading day before the event:[1]

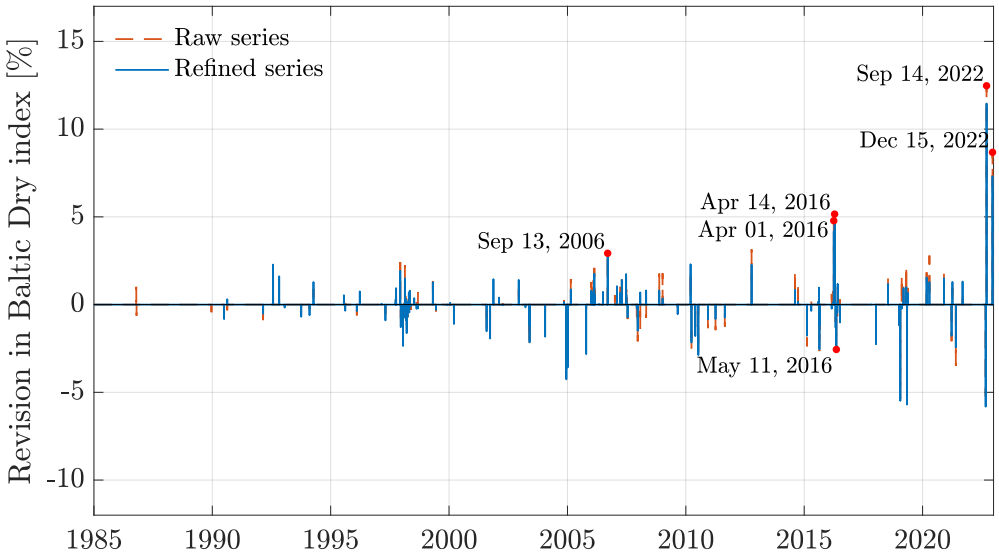
$$SCSurprise_d = \frac{P_d^{\text{BDI}} - P_{d-1}^{BDI}}{P_{d-1}^{\text{BDI}}}, \tag{1}$$

where d indicates the date of the event, and P_d^{BDI} is the BDI price. Note that if an event is partially anticipated, this will isolate the unexpected component of the given event, provided that these expectations are priced in the market.

Figure 4 shows the shipping cost surprise series at the daily frequency. Events that disrupt shipping traffic can have a significant impact on shipping costs, with several events moving shipping costs in excess of 3 percent. For instance, on September 13, 2006, an Egyptian dredger sank in the Suez Canal, causing a temporary closure of the waterway as a rescue operation was under way to find missing crew members. This resulted in an increase in shipping costs of 2.9 percent.

[1]Typically, event reporting takes place on the same day as the event itself. However, when the event reporting occurs after the event, we use the event reporting day to compute the surprise, since our identification strategy relies on the event being monitored by market participants. Additionally, if trading did not take place on the event reporting day, we use the next trading day to compute the surprise.

Figure 4: Shipping Cost Surprise Series



On April 1, 2016 and April 14, 2016, reporting on the extensions of draft restrictions by the ACP due to El Nino-related droughts caused shipping costs to increase by 4.8 percent and 5.2 percent, respectively. On May 11, 2016, the draft restrictions were postponed due to rainfall, which led to a fall in shipping costs by around 3 percent. The latter is an example of a negative shipping cost surprise. Negative surprises may arise either from events that ease previous restrictions or from news indiciating that a disruption is less severe than previously anticipated. However, we will assess the robustness of our results when only focusing on positive surprises.

Finally, on September 14, 2022, reporting of a rare overflow at the Panama Canal's Gatun Locks, that temporarily blocked the west lane, resulted in an increase in shipping costs of 12.5 percent. On December 15, 2022, traffic at the Panama Canal's Miraflores locks was temporarily suspended due to a fire, again leading to an increase in shipping costs of 8.7 percent.

Predictability of shipping cost surprises. An influential literature finds that in the monetary policy context, high-frequency surprises are predictable based on publicly available macroeconomic and financial data preceding the policy announcement (Bauer and Swanson, 2023; Cieslak, 2018; Miranda-Agrippino and Ricco, 2021). This predictability challenges the interpretation of such surprises as primitive "shocks" and may bias estimates of their dynamic effects.

Are shipping cost surprises also predictable based on past macroeconomic and finan-

cial variables? To assess this, we regress the daily surprise series on relevant information available before the event:

$$SCSurprise_d = \alpha + \beta' X_{d-} + \eta_d, \tag{2}$$

where d indexes days with shipping disruptions, $SCSurprise_d$ denotes the shipping cost surprise series, and X_{d-} is a set of predictors known before the event day d, as indicated by the subscript $d-$.

As predictors, we consider a wide range of macroeconomic and financial variables. For macroeconomic and financial indicators, we include the surprise components of the latest U.S. industrial production, ISM Purchasing Managers' Index (PMI), producer price index, and the trade balance releases prior to each event. These surprises are defined as the difference between the actual release and Bloomberg survey expectations. We also include the log change in the S&P 500 index and the yield curve slope, measured over the three months leading up to the event. For commodity markets, we add the three-month log changes in the WTI crude and the coal price. Finally, to account for geopolitical risk, we include the three-month change in the index by Caldara and Iacoviello (2018).

Table 2 presents the results. There is limited evidence that shipping cost surprises are predictable by macroeconomic and financial variables. The R^2 is generally low, ranging from 0.03 to 0.09 across specifications. The only predictor that is statististically significant at conventional levels is the ISM surprise. This is not necessarily problematic, as it may stem from plausibly exogenous factors like unusual weather patterns. Alternatively, a high ISM may indicate tighter supply chains, thereby making disruptions more binding or increasing their salience.

To account for this potential predictability, we follow the approach by Bauer and Swanson (2023). Specifically, we construct a refined shipping cost surprise series as the residual from the predictive regression (2), controlling for the full information set (d). The resulting series $\widetilde{SCSurprise}_d = \eta_d$, shown as the blue bars in Figure 4, closely tracks the raw series, with a correlation coefficient of over 0.95.

Aggregation and additional diagnostics. Because our outcome variables of interest are only available at the monthly frequency, we aggregate the daily surprises to a monthly series as follows:

$$SCSurprise_t = \sum_{k=1}^{62} \beta_k SCSurprise_{t_d - k}, \tag{3}$$

Table 2: Predictability of Shipping Cost Surprises

Shipping cost surprise:	(a) Macro news	(b) Financials	(c) Commodities	(d) Other
IP surprise	-0.068	-0.276	-0.226	-0.225
	(0.410)	(0.364)	(0.326)	(0.332)
ISM surprise	0.152	0.169	0.216	0.216
	(0.095)	(0.107)	(0.103)	(0.103)
PPI surprise	-0.056	-0.020	0.115	0.113
	(0.534)	(0.511)	(0.563)	(0.578)
Trade balance surprise	0.076	0.099	0.104	0.104
	(0.066)	(0.073)	(0.073)	(0.073)
S&P 500 (3M log change)		-2.163	-1.036	-1.019
		(2.653)	(2.753)	(2.591)
Yield curve slope (3M change)		-0.804	-0.653	-0.652
		(0.719)	(0.774)	(0.769)
WTI price (3M log change)			0.040	0.045
			(0.777)	(0.743)
Coal price (3M log change)			-2.724	-2.731
			(2.169)	(2.105)
Geopolitical risk (3M log change)				0.000
				(0.003)
R^2	0.030	0.067	0.092	0.092
Adj. R^2	0.000	0.023	0.034	0.026

Notes: Estimated coefficients β, R^2 and adj. R^2 from predictive regressions (2) of shipping cost surprises. The predictors X are observed prior to the event and include: the surprise component of the most recent U.S. industrial production, ISM PMI, producer price index, and trade balance releases in column (a); column (b) adds the three-month change in the (log) S&P 500 and the yield curve slope; column (c) adds the three-month log change in WTI and coal price; column (d) adds three-month log change in geopolitical risk. Robust standard errors in parentheses.

where t is the month and t_d indexes time at daily frequency. β_k are triangular weights as in Gertler and Karadi (2015). By construction, in months without any events, the surprise series takes zero value. Effectively, this approach weights an event surprise by the share of calendar days remaining in the month, and attributing the remaining portion of the surprise to the next month. For example, if a surprise occurs on the 7th calendar day of a month with 30 days, 80% of the surprise will be assigned to the current month and 20% of the surprise will be assigned to the next month.[2]

To account for potential serial correlation that the temporal aggregation may introduce, we follow the approach by Miranda-Agrippino and Ricco (2021) and purge the

[2]We implement this by first cumulating the surprises on all events days to obtain a daily cumulative surprise series. Next, we take monthly averages of the daily cumulative surprise series. Finally, we first difference the series to obtain the monthly average surprise series.

monthly surprise series by regressing on its lags and using the residual:

$$SCSurprise_t = \phi_0 + \sum_{j=1}^{12} \phi_j SCSurprise_{t-j} + SCSurprise_t^{\perp} \tag{4}$$

We perform a number of diagnostic checks on the surprise series as proposed in Ramey (2016), in particular with regards to autocorrelation, forecastability, and correlation with other structural shocks. We find no evidence that the series is serially correlated. The p-value for the Q-statistic that all autocorrelations are zero is 0.99. We also find little evidence that macroeconomic or financial variables have any power in forecasting the surprise series. For all variables considered, the p-values for the Granger causality test are far above conventional significance levels, with the joint test having a p-value of 0.86. Finally, we show that the surprise series is uncorrelated with other structural shock measures from the literature, including oil, productivity, news, monetary policy, uncertainty, financial, and fiscal policy shocks. Overall, this evidence supports the validity of the shipping cost surprise series. The corresponding figures and tables can be found in online Appendix B.

3. Econometric Approach

As illustrated above, the shipping cost surprise series has many desirable properties. Nonetheless, it is only an imperfect measure of the shock of interest because it does not capture all relevant disruptions in global supply chains and could be measured with error (Stock and Watson, 2018). Therefore, we do not use it as a direct shock measure but as an *instrument*. Provided that the surprise series is correlated with the supply chain shock but uncorrelated with all other shocks, we can use it to estimate the dynamic causal effects of a structural supply chain shock.

A challenge in estimating the dynamic causal effects using high-frequency surprises is the so-called power problem (Nakamura and Steinsson, 2018). Over the impulse horizon, macroeconomic variables are influenced by a myriad of other shocks, while high-frequency shipping cost surprises explain only a small share of the fluctuations in shipping rates—resulting in a low signal-to-noise ratio. This makes it difficult to directly estimate macroeconomic effects of high-frequency shipping cost surprises using local projections à la Jordà (2005).

To address this challenge, we rely on VAR techniques for estimation, using the external instruments approach (Mertens and Ravn, 2013; Stock, 2008; Stock and Watson, 2012).

3.1. Framework

We are interested in modeling global shipping markets and the U.S. economy jointly. Let $\mathbf{y}_t$ denote a $n \times 1$ vector of monthly time series. We assume that the dynamics of $\mathbf{y}_t$ can be characterized by the following structural vector moving-average representation:

$$\mathbf{y}_t = \mathbf{B}(L)\mathbf{S}\boldsymbol{\varepsilon}_t, \tag{5}$$

where $\boldsymbol{\varepsilon}_t$ is a vector of mutually uncorrelated structural shocks driving the economy, $\mathbf{B}(L) \equiv \mathbf{I} + \mathbf{B}_1 L + \mathbf{B}_2 L^2 + \ldots$ is a matrix lag polynomial, and $\mathbf{S}$ is the structural impact matrix.

Assuming that the vector-moving average process (5) is invertible, it admits the following VAR representation:

$$\mathbf{A}(L)\mathbf{y}_t = \mathbf{S}\boldsymbol{\varepsilon}_t = \mathbf{u}_t, \tag{6}$$

where $\mathbf{u}_t$ is a $n \times 1$ vector of reduced-form innovations with variance-covariance matrix $\text{Var}(\mathbf{u}_t) = \boldsymbol{\Sigma}$ and $\mathbf{A}(L) \equiv \mathbf{I} - \mathbf{A}_1 L - \ldots$ is a matrix lag polynomial. Truncating the VAR to order p, we can estimate the model using standard techniques and recover an estimate of $\mathbf{A}(L)$.

We want to identify the causal impact of a single shock. Without loss of generality, let us denote the supply chain shock as the first shock in the VAR, $\varepsilon_{1,t}$. Our aim is to identify the structural impact vector $\mathbf{s}_1$, which corresponds to the first column of $\mathbf{S}$.

External instrument approach. Identification using external instruments works as follows. Suppose there is an external instrument available, z_t. In the application at hand, z_t is the shipping cost surprise series. For z_t to be a valid instrument, we need:

$$\mathbb{E}[z_t \varepsilon_{1,t}] = \alpha \neq 0 \tag{7}$$

$$\mathbb{E}[z_t \boldsymbol{\varepsilon}_{2:n,t}] = \mathbf{0}, \tag{8}$$

where $\varepsilon_{1,t}$ is the supply chain shock and $\boldsymbol{\varepsilon}_{2:n,t}$ is a $(n-1) \times 1$ vector consisting of the other structural shocks. Assumption (7) is the relevance requirement and assumption (8) is the exogeneity condition. These assumptions identify the structural impact vector $\mathbf{s}_1$ up to

sign and scale:

$$\mathbf{s}_1 \equiv \boldsymbol{\theta}_0 \propto \frac{\mathbb{E}[z_t \mathbf{u}_t]}{\mathbb{E}[z_t u_{1,t}]}, \tag{9}$$

provided that $E[z_t u_{1,t}] \neq 0$. Note that to identify the relative impact effects, we do not need to assume invertibility. Invertibility is only required for the dynamic effects beyond impact.[3]

To facilitate interpretation, we scale the structural impact vector such that the shock corresponds to a 10 percent increase in shipping costs. We implement the estimator with a 2SLS procedure and estimate the coefficients above by regressing $\hat{\mathbf{u}}_t$ on $\hat{u}_{1,t}$ using z_t as the instrument. To conduct inference, we employ a residual-based moving block bootstrap, as proposed by Jentsch and Lunsford (2019).

Relaxing VAR assumptions. The VAR approach improves precision, allowing for sharper inference. However, it relies on two potentially restrictive assumptions. The first is invertibility, meaning that the model incorporates all relevant information needed to recover the structural shocks of interest. The second pertains to the dynamic VAR structure, with the key assumption being that a finite-order VAR adequately approximates the dynamics of the data generating process well. We perform two exercises to assess how restrictive these assumptions are.

First, we alternatively estimate the responses using the internal instrument approach (Plagborg-Møller and Wolf, 2019). This approach does not rely on invertibility but instead assumes that the instrument is orthogonal to leads and lags of the structural shocks:

$$\mathbb{E}[z_t \boldsymbol{\varepsilon}_{t+j}] = \mathbf{0}, \quad \text{for } j \neq 0. \tag{10}$$

Together with the exogeneity and relevance requirement, this identifies the dynamic causal effects of interest. The approach can be implemented by augmenting the VAR with the instrument ordered first, $\bar{\mathbf{y}}_t = (z_t, \mathbf{y}_t')'$, and computing the impulse responses to the first orthogonalized innovation, $\bar{\mathbf{s}}_1 = [\text{chol}(\bar{\boldsymbol{\Sigma}})]_{\cdot,1} / [\text{chol}(\bar{\boldsymbol{\Sigma}})]_{1,1}$.

Second, we estimate the impulse responses to the supply chain VAR shock using local projections. This approach directly estimates the dynamic responses and does not rely on the VAR structure, making it less prone to lag truncation bias. Specifically, we first

[3]To be more precise, the VAR does not have to be fully invertible for identification with external instruments: it suffices if the shock of interest is invertible in combination with a limited lead-lag exogeneity condition (Miranda-Agrippino and Ricco, 2018).

extract the supply chain shock from the monthly VAR as $\varepsilon_{1,t} = \mathbf{s}_1' \mathbf{\Sigma}^{-1} \mathbf{u}_t$ (for a derivation, see Stock and Watson, 2018). Next, we estimate the effects for the additional variables of interest y_i using simple local projections:

$$y_{i,t+h} = \alpha^i_{h,0} + \theta^i_h \varepsilon_{1,t} + \beta^i_{h,1} y_{i,t-1} + \ldots + \beta^i_{h,p} y_{i,t-p} + \xi_{i,t,h}, \tag{11}$$

where θ^i_h is the effect on variable i at horizon h. Note that while this is a more robust way to estimate the dynamic responses, it still retains the assumption of (partial) invertibility.

Estimating effects on additional outcome variables. To analyze the effects on a wider set of outcome variables, we adopt the following approach. For monthly variables, we augment our baseline VAR by the variable of interest and map out the response as in (Gertler and Karadi, 2015). For variables at lower frequencies, we rely on the local projections approach outlined above. To fix ideas, we aggregate the shock $\varepsilon_{1,t}$ by summing over the respective months before running the local projections at the lower frequency. This mitigates the problem that high-frequency instruments, when aggregated to the quarterly or annual frequency, often lack the power to credibly estimate the effects of interest (Nakamura and Steinsson, 2018).

Empirical specification. The baseline specification includes 8 variables, consisting of a global supply chain block containing the real shipping cost (measured using the BDI), real commodity price index, global shipping capacity, and geopolitical risk index, and a block for the U.S. economy including the U.S. industrial production, consumer price index (CPI), three-month treasury yield and real effective exchange rate.[4] Detailed information on the data, including sources, can be found in Appendix A.

We use monthly data spanning the period from 1970 to 2022 and estimate the VAR in levels, following Sims, Stock, and Watson (1990). Besides the policy indicator, all variables enter in log-levels. The lag order is set to 12 and the deterministic terms include a constant and a linear trend.

[4]Unfortunately, the global shipping capacity data is only available at the annual frequency. We therefore construct a monthly measure using the Chow-Lin temporal disaggregation method with indicators from the Quilis (2020) code suite. As the relevant monthly indicators, we include the world industrial production and oil price.

4. The Macroeconomic Impact of Supply Chain Shocks

How do supply chain shocks affect the global shipping market and the macroeconomy? In this section, we discuss the results based on our baseline external instruments VAR model.

First stage. The main identifying assumption behind the external instruments approach is that the instrument is correlated with the structural shock of interest but uncorrelated with all other structural shocks. This assumption is not testable, but we select the disruptions underlying our surprise series carefully to isolate some variation in shipping rates that is plausibly exogenous.

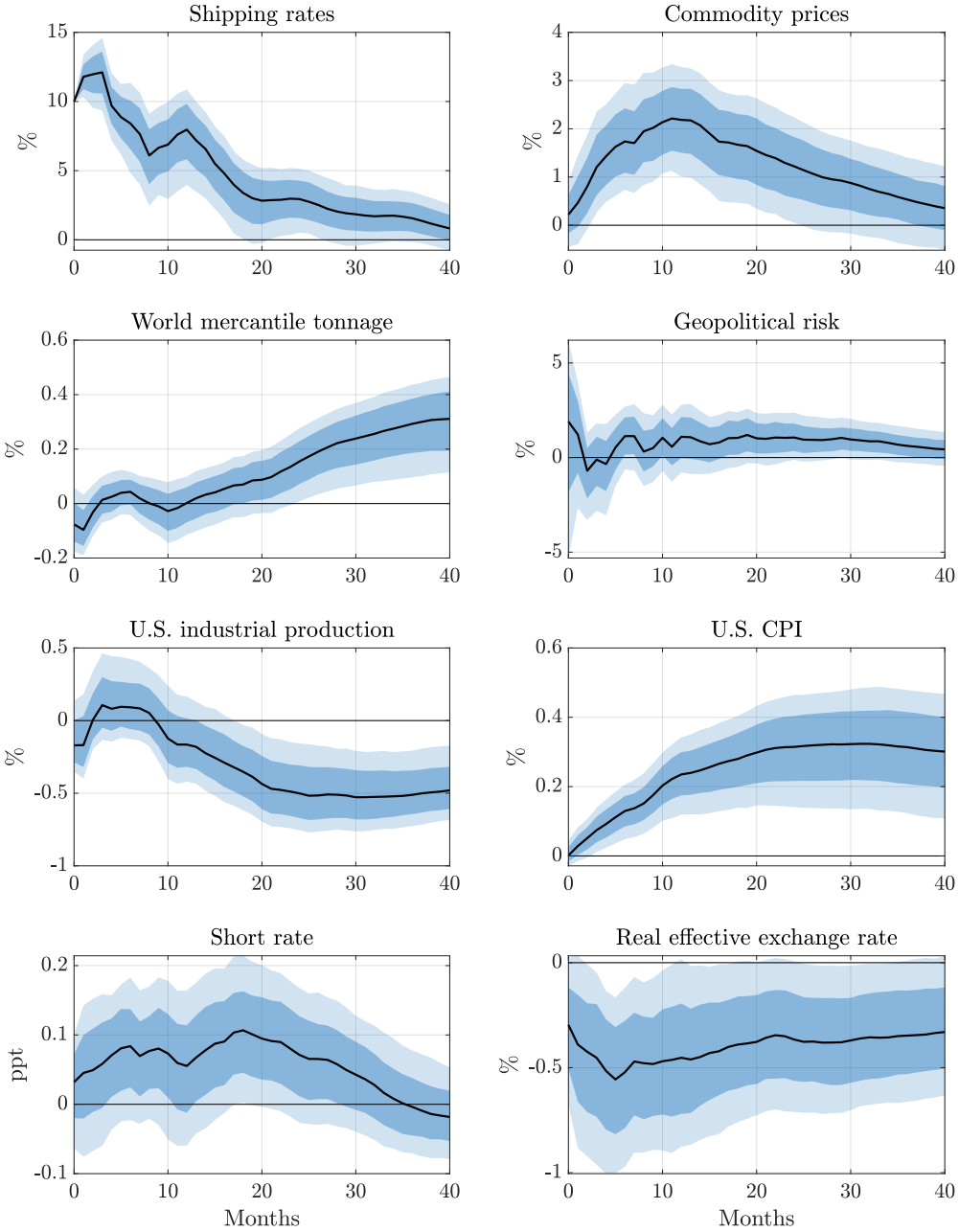
However, even if the surprise series is exogenous, standard inference will not produce reliable results when the instrument and the shock are only weakly correlated. In a first step, it is thus important to test the *strength* of the instrument. This can be done using an F-test in the first-stage regression of the shipping cost residual from the VAR on the instrument (Montiel Olea, Stock, and Watson, 2016). The shipping cost surprise series is a strong instrument, with a heteroskedasticity-robust F-statistic of 24.44. As this is above conventional critical values, the instrument appears to be sufficiently strong to conduct standard inference.

Macroeconomic effects. Figure 5 shows the impulse responses to the identified supply chain shock, normalized to increase the real shipping cost by 10 percent on impact. In each panel, the solid black line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

A disruptive supply chain shock leads to a strong increase in shipping rates that persists for months beyond the initial event. Interestingly, our analysis shows that these effects last significantly longer than the duration of the shipping disruptions included in our instrument. The main reason is that a disruptive event, even if only relatively short-lasting, creates substantial ripple effects throughout the entire shipping market. Ships must be rerouted, reducing available capacity for scheduled shipments, creating bottlenecks at alternative ports, and disrupting the tightly coordinated global shipping network. These cascading effects ultimately impact global shipping capacity and pricing for months beyond the initial disruption.

The rise in shipping costs has important consequences on shipping markets and global commerce. Commodity prices increase significantly, albeit the peak effect only materializes with some lag. The elevated shipping costs create an incentive to expand shipping

Figure 5: Impulse Responses to a Supply Chain Shock



First stage: Robust F-statistic: 24.44, R^2: 4.18%, Adjusted R^2: 4.03%

Notes: Impulse responses to a supply chain shock, normalized to increase real shipping costs by 10 percent on impact. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

capacity, as can be seen from the sluggish increase in world mercantile tonnage. Finally, the shock has no significant effect on geopolitical risk. This is reassuring as we purposefully abstract from disruptive events related to geopolitical tensions as they may affect the global economy through channels unrelated to supply chains.

Higher shipping costs also put pressure on the economy. U.S. industrial production falls significantly and U.S. consumer prices increase persistently. The supply chain shock has thus stagflationary effects, creating a trade-off for monetary policy. This is reflected in the response of the short-term interest rate, which tends to increase even though the response is not statistically significant. Finally, the real effective exchange rate falls, implying a stark depreciation of the dollar.

Quantitatively, a supply chain shock increasing shipping rates by 10 percent leads to an increase in commodity prices by about 2 percent and an increase in the world merchant fleet by 0.3 percent, at peak. U.S. industrial production falls by around 0.5 percent, the U.S CPI increases by 0.3 percent, and the real effective exchange rate falls by 0.5 percent. These impacts are considerable and comparable with the economic impacts of other supply-side shocks, such as commodity price shocks (Baumeister and Hamilton, 2019; Känzig, 2021; Kilian, 2009). However, the sluggish increase in commodity prices together with the delayed increase in the world merchant fleet, suggests that we are not merely picking up commodity price shocks such as oil price shocks, which are known to have more immediate energy price impacts.

4.1. Addressing Identification Concerns

In this section, we assess the robustness of our results with respect to some of the key assumptions underlying our empirical approach. We also discuss potential identification concerns regarding our instrument.

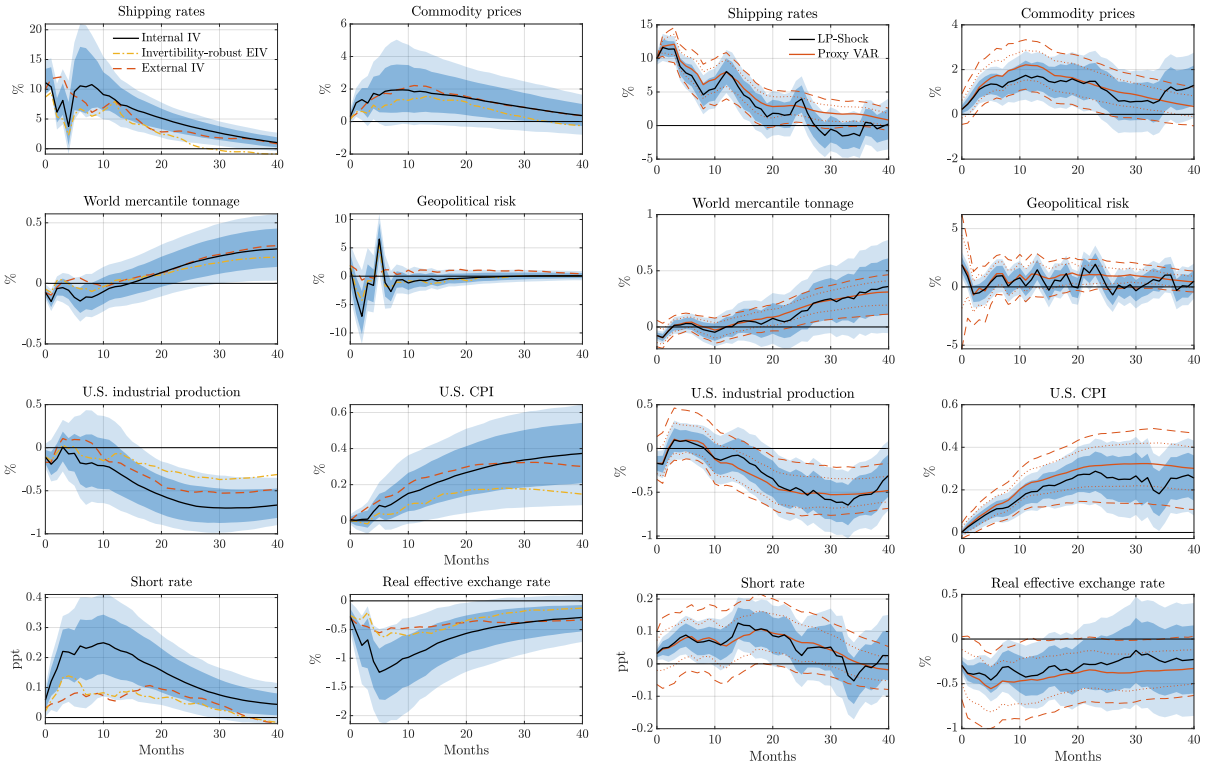
First, we relax the invertibility requirement, estimating the responses based on invertibility-robust methods. In addition to the internal instruments approach by Plagborg-Møller and Wolf (2019), we also show results from an invertibility-robust external instruments approach (Forni, Gambetti, and Ricco, 2022). The results are shown in Figure 6a. We can see that the responses turn out to be very similar to our baseline external instruments results.

Second, we assess the extent of lag truncation bias by estimating the dynamic responses based on local projections. The responses are very similar to our baseline responses, suggesting that our dynamic VAR structure is flexible enough to capture the dynamics in shipping markets and the U.S. economy adequately. In the appendix, we

further show that our results are robust to varying the lag order in our VAR model (see Figure C.10).

Figure 6: Relaxing VAR Assumptions

(a) Invertibility-robust Responses (b) Assessing Lag-truncation Bias



Notes: Impulse responses to a supply chain shock, normalized to increase real shipping costs by 10 percent on impact. Panel (a) shows the responses under different invertibility-robust approaches. Panel (b) compares the responses estimated based on VARs and local projections. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

We also address a number of additional concerns regarding our identification strategy. A first concern is that collisions at the martitime choke points we consider could be more likely to occur during periods of economic expansion, potentially introducing some endogenous variation in our instrument. Reassuringly, our results turn out to be robust when excluding collision-related events, see Appendix Figure C.1.

Second, disruptions in the Suez Canal may coincide with major geopolitical developments, raising concerns about potential confounders. In our baseline specification, we already control for a news-based geopolitical risk index. To further mitigate these concerns, we show that our results are robust to only using events in the Panama Canal, see Appendix Figure C.6. Including the Suez canal events yields similar point estimates but helps improves precision.

Third, we consider the role of major macroeconomic events that could confound our estimates, such as the oil price shocks of the 1970s, the global financial crisis (GFC), or the Russian invasion of Ukraine. We confirm that our results are robust to excluding the 1970s and the COVID-19 period, and to controlling explicitly for the GFC using a dummy variable. None of these large macro shocks appear to drive our results, see Appendix Figures C.8-C.9 and C.11.

A fourth potential concern is that negative surprises in shipping costs may coincide with adverse macroeconomic news, confounding their interpretation as supply chain shocks. To mitigate this concern, we show that results are robust to keeping only positive shipping disruptions, see Appendix Figure C.7. More broadly, concerns about background noise—i.e., other confounding developments occurring within the event window—are alleviated by the robustness of our results to varying the length of the event window (Appendix Figure C.5).

Finally, we explore how the predictability in our shipping cost surprises affects the results. We find consistent effects when restricting the sample to the first event in each sequence—those that are arguably least predictable—as well as when we forgo any attempt to remove predictability altogether, see Appendix Figures C.3 and C.4. This suggests that our findings are not mechanically driven by anticipatory behavior.

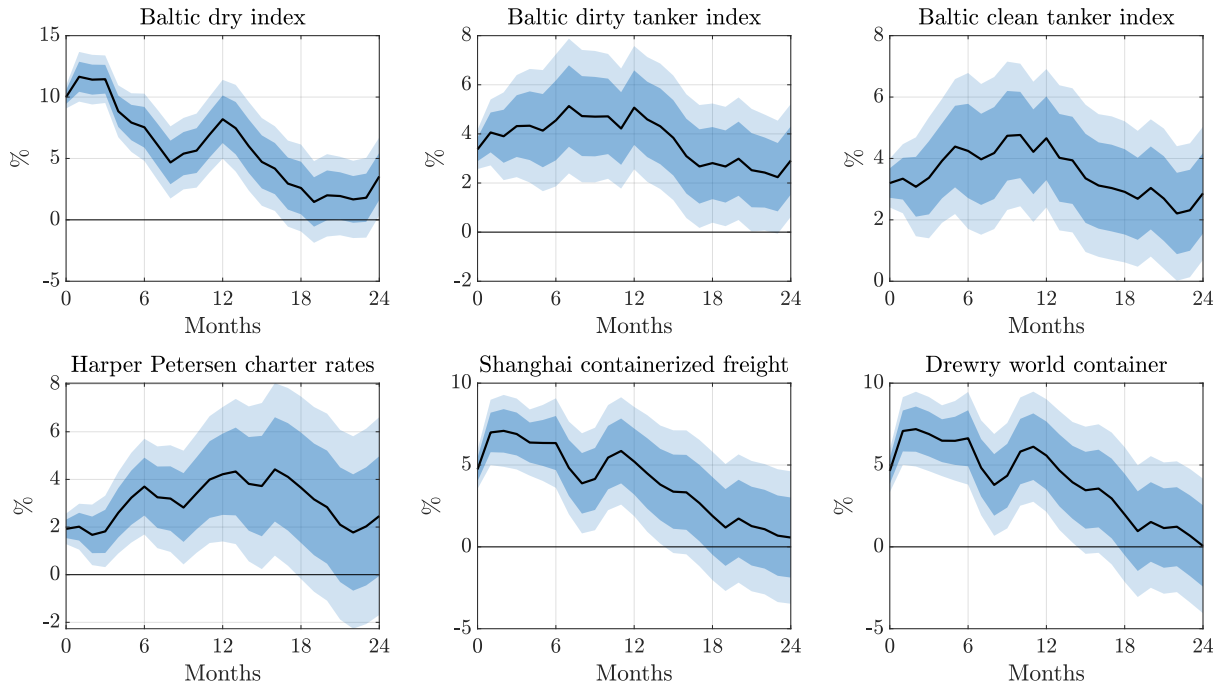
4.2. Wider Effects and Propagation Channels

To strengthen our interpretation of a supply chain shock, we study the effects of the shock on a wider range of financial macroeconomic variables. We follow the approach outlined in Section 3.1 to compute the impulse responses for additional variables of interest.

Impact on shipping costs. We begin by documenting that the identified shock leads to a broad-based increase in shipping costs across different segments of maritime transport. This is important for interpretation. Our baseline measure of shipping costs relies on the BDI, which captures dry bulk shipping rates. However, the disruptions we study—such as blockages at key maritime choke points—are not specific to bulk shipping and should affect the entire shipping network, including tanker and containerized freight markets.

To assess the generality of the shock, we extend our analysis to a range of alternative shipping cost indices covering tanker, charter, and containerized freight markets. Figure 7 shows that the supply chain shock induces a significant and persistent increase in shipping rates across all segments. In addition to the BDI, both clean and dirty tanker rates, charter rates, and container freight indices rise on impact and remain elevated for several

Figure 7: Broader Effects on Shipping Cost



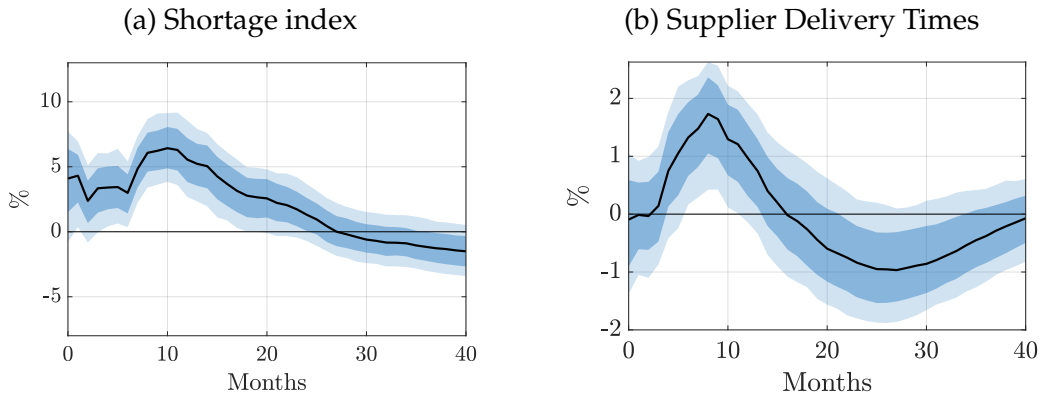
Notes: Impulse responses to a supply chain shock, normalized to increase real shipping costs by 10 percent on impact. The IRFs are estimated by local projections (11) on the aggregated supply chain shock extracted from our baseline external instruments VAR. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

months.

These results indicate that the identified shock captures a disruption to global shipping conditions rather than movements specific to dry bulk markets. Having established that the shock leads to a broad-based increase in shipping costs, we next turn to downstream manifestations of supply chain stress.

Shortages. To corroborate our interpretation of a supply chain shock, we first assess whether the shock is associated with significant delays in deliveries and shortages. To that end, we rely on the supplier delivery times indicator from the ISM and the newspaper-based supply chain shortage indices constructed by Caldara, Iacoviello, and Yu (2024). From Figure 8, we can see that the supply chain shock leads to a significant increase in delivery times and supply chain shortages—consistent with the notion that supply chain disruptions delay relevant shipments and cause shortages down the line. Looking into the components of the shortage index in Appendix Figure D.1, we find that shortages are particularly pronounced for industrial materials and energy.

Figure 8: Effects on Supply Chain Shortages and Delivery Times



Notes: Impulse responses to a supply chain shock, normalized to increase real shipping costs by 10 percent on impact. The IRFs are obtained by using our baseline VAR and augmenting it by the variable of interest. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Geopolitical risk. Given the significant impact on energy shortages, one may be concerned that our approach largely captures geopolitical oil supply risk. This is why we did not include any disruptive events in the Strait of Hormuz. In selecting our events, we thus put great care into excluding disruptions associated with geopolitical developments and reassuringly, we find that our supply chain shocks have no significant effect on geopolitical risk. We also show that the supply chain shock does not impact other measures of risk

and uncertainty, such as economic and trade policy uncertainty and crude oil volatility (see Figure D.2 in the appendix).

Producer prices, consumer prices, and expectations. We have seen that supply chain shocks lead to an increase in commodity and consumer prices. We now examine the components of producer and consumer prices to identify which categories are most affected. In Figure 9a, we analyze the responses of different producer commodity prices, including farm products, industrial commodities, and energy. All three components show a significant increase, with industrial commodities and energy prices demonstrating a more persistent increase compared to farm products.

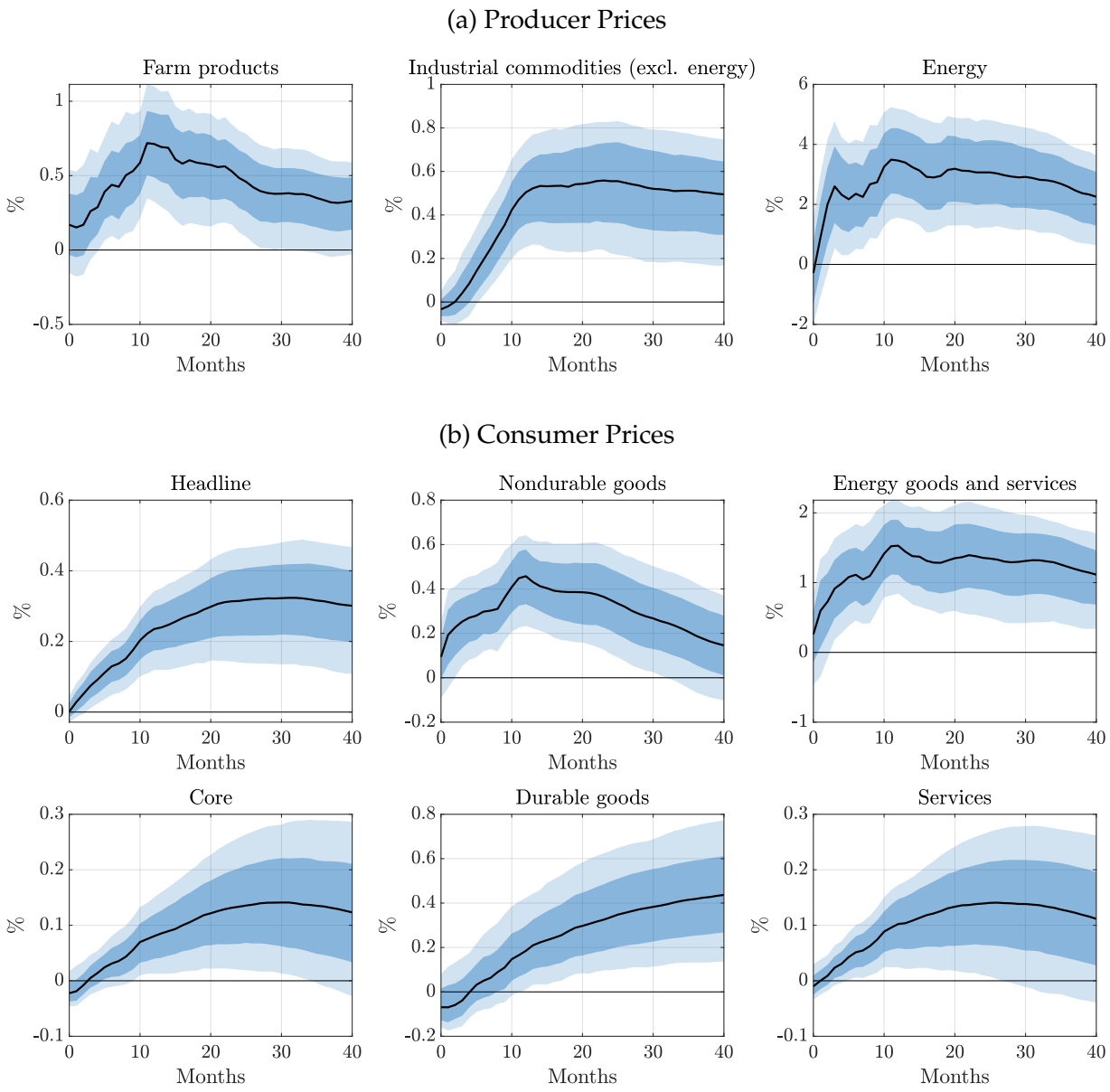
In terms of magnitude, energy prices increase the most, with a peak response of around 2 percent. This increase can be attributed to two factors. First, oil tankers account for approximately 30 percent of global fleet capacity, and an estimated 76 percent of world oil trade relies on seaborne routes. Disruptions to shipping introduce delays in oil transport, thereby disrupting oil supply and driving up prices. Second, vessels must undertake longer journeys when key maritime chokepoints are affected, leading to an increase in their fuel demand and consumption. These factors together contribute to the sustained rise in energy prices.

The increases in the producer prices are passed onto to consumers to a significant extent. In Figure 9b, we show the responses of major consumer price components, including core, nondurable, energy, durable, and service prices, alongside the headline measure from our baseline specification. The responses of nondurable and energy prices qualitatively resemble the response of producer prices and exhibit a more front-loaded increase compared to the headline measure. The price of services and durables also increase significantly, with the durable price response displaying substantial persistence. Consequently, we also document a sluggish but significant rise in core consumer prices.

Supply chain shocks not only increase actual prices, they also translate into higher inflation expectations. Figure 10 shows the inflation expectations for consumers from the Michigan survey and for forecasters from the Survey of Professional Forecasters (SPF). We can see that household inflation expectations increase persistently. Interestingly, the inflation expectations of professional forecasters do not respond.

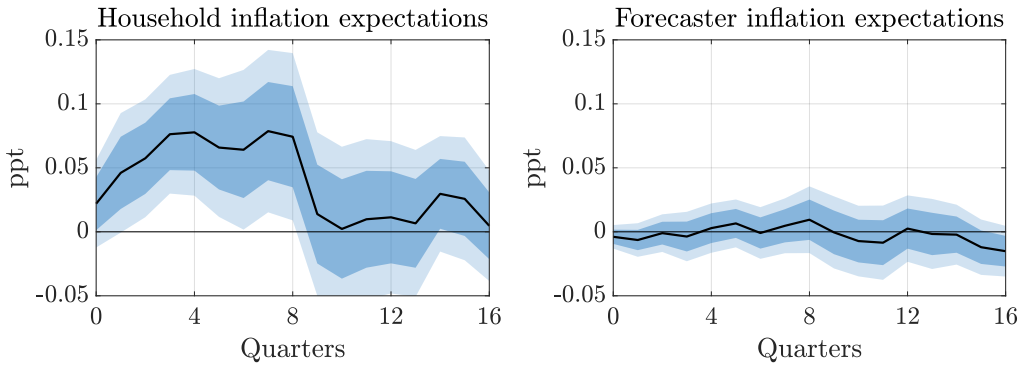
Economic activity and trade. Supply chain disruptions have substantial effects on both real activity and external balances. Figure 11a shows that a supply chain shock leads to a broad-based decline in economic activity. Real GDP falls by about 0.25 percent at peak, with investment and consumption declining by around 1 percent and 0.2 percent, respec-

Figure 9: Impact on Producer and Consumer Prices



Notes: Impulse responses to a supply chain shock, normalized to increase real shipping costs by 10 percent on impact. The IRFs are obtained by using our baseline VAR and augmenting it by the variable of interest. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure 10: Inflation Expectations



Notes: Impulse responses to a supply chain shock, normalized to increase real shipping costs by 10 percent on impact. The IRFs are obtained by using our baseline VAR and augmenting it by the variable of interest. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

tively. These aggregate responses reflect disruptions to production and higher input costs that weigh on demand and investment.

Turning to external adjustment, the shock also has pronounced effects on trade. Figure 11b shows that the terms of trade deteriorate significantly, driven by a sharp increase in import prices. At the same time, the trade balance improves, consistent with the depreciation of the dollar and a contraction in imports. Together, these results highlight that supply chain shocks propagate through both domestic demand and international relative prices.

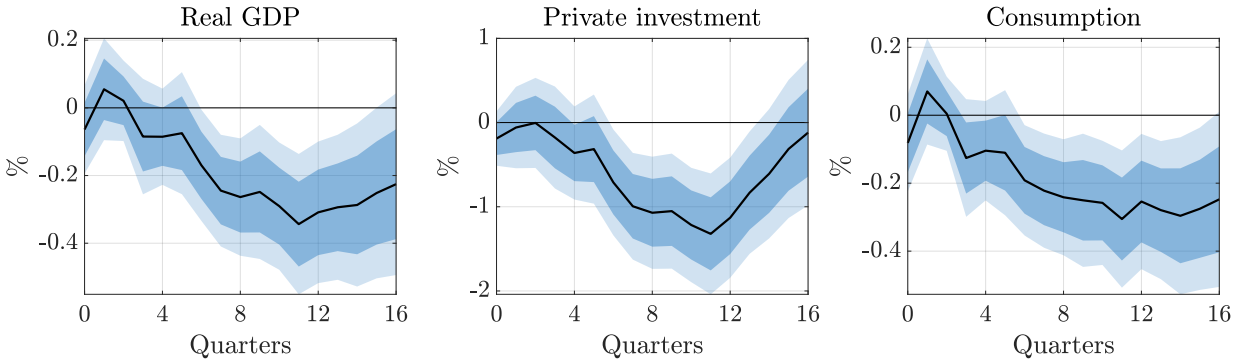
4.3. Understanding the Recent Inflationary Episode

We use our identified supply chain shocks to revisit the recent surge in inflation and assess the quantitative contribution to macroeconomic dynamics during this period. To this end, we simulate the economy under the sequence of estimated supply chain shocks while setting all other structural shocks to zero. This exercise provides a counterfactual estimate of how inflation, commodity prices, and real activity would have evolved in the absence of other shocks. The results are shown in Figure 12.

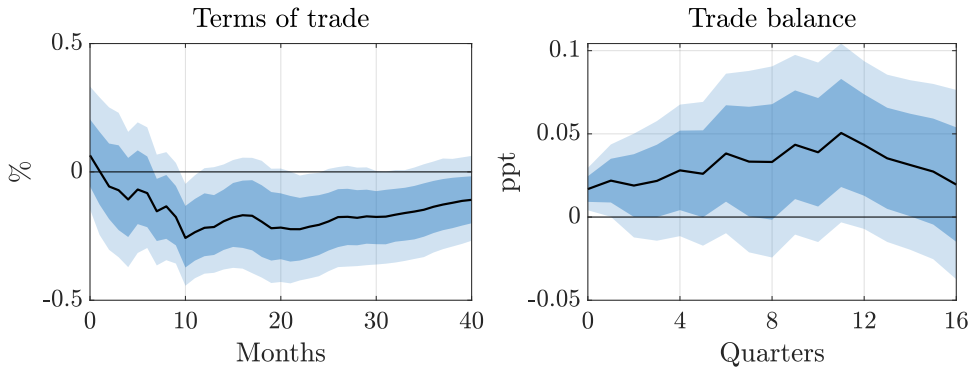
We find that supply chain disruptions contribute meaningfully to the variation in inflation over the 2020–2022 period. In particular, they help explain a substantial share of the rise in inflation through 2021, consistent with the timing of widespread logistical bottlenecks and maritime stress. However, the magnitude of their contribution is insufficient to account for the full extent of the inflation surge. Our results suggest that while supply chain shocks were an important factor early on, they cannot explain the sharp acceleration

Figure 11: Economic Activity and Trade Effects

(a) Macroeconomic Aggregates

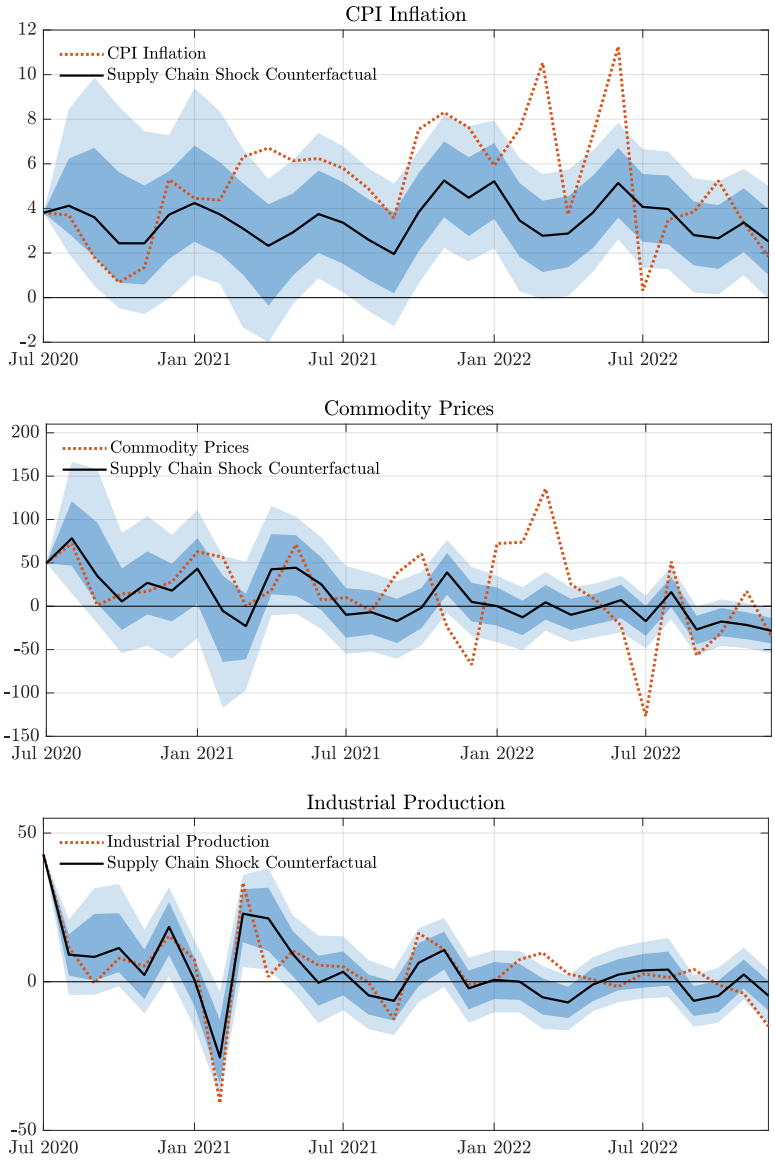


(b) Terms of Trade and Trade Balance



Notes: Impulse responses to a supply chain shock, normalized to increase real shipping costs by 10 percent on impact. The IRFs in Panel a are estimated by local projections (11) on the aggregated supply chain shock extracted from our baseline external instruments VAR. The IRFs in Panel b are obtained from our baseline VAR by augmenting the system with the variable of interest. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure 12: The Role of Supply Chain Shocks in the Recent Inflationary Episode



Notes: Counterfactual evolution of CPI inflation, commodity prices inflation and industrial production growth when turning off all other shocks but supply chain shocks from mid-2020 to 2022 (black line), together with the actual evolution of these variables (dashed red line). The dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

in inflation observed in 2022.

The same pattern is evident in commodity price dynamics. Supply chain disruptions explain a sizable portion of the fluctuations in commodity prices throughout 2021, reflecting their role in affecting global transportation costs and intermediate input availability. Yet, they fall short of accounting for the drastic commodity price spikes that followed the Russian invasion of Ukraine, pointing instead to additional geopolitical or supply-side factors unrelated to logistics.

Overall, we conclude that supply chain shocks played some role in the recent inflationary episode but cannot account for the peak inflation rates observed in 2022. This finding is in line with recent evidence highlighting the importance of expansionary demand-side policies—such as fiscal stimulus and accommodative monetary policy (Giannone and Primiceri, 2024)—as well as commodity supply shocks, particularly in energy and food markets (Gagliardone and Gertler, 2023).

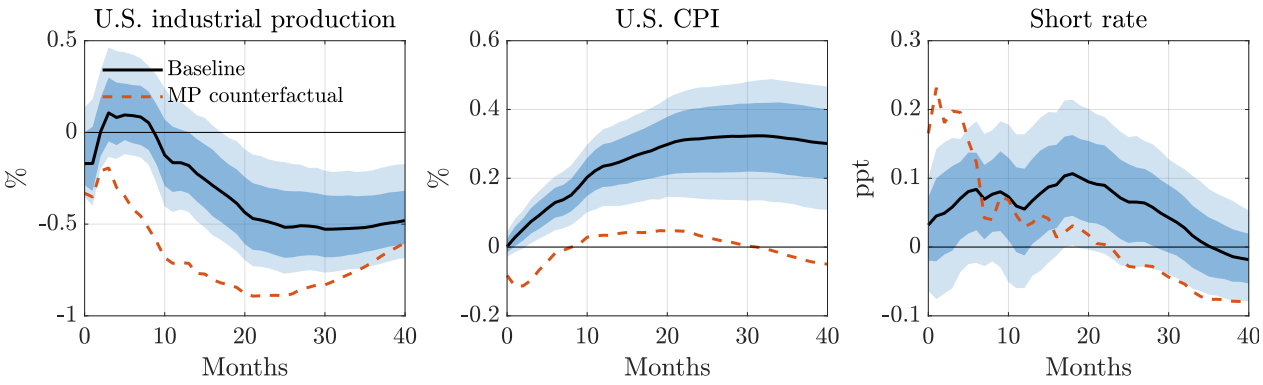
That said, supply chain shocks had a more pronounced effect on real economic activity. Our analysis shows that they were an important drag on industrial production throughout 2021, a period marked by intense global logistics disruptions. This suggests that while supply-side bottlenecks had limited effects on prices, they significantly impaired production and contributed to the uneven sectoral recovery in the aftermath of the pandemic.

Finally, we assess the role of monetary policy in shaping the macroeconomic transmission of supply chain disruptions. To this end, we conduct a counterfactual policy simulation using the McKay and Wolf (2023) approach, which allows us to evaluate how supply chain shocks propagate under alternative monetary policy responses. The idea is to leverage estimated impulse responses to monetary policy shocks to impose a counterfactual monetary response to supply chain shocks. By only using a combination of shocks on impact, the contemplated counterfactual policy is incorporated in private-sector expectations ex-ante and thus robust to the Lucas critique. To implement the approach, we rely on the identified monetary policy shocks by Bauer and Swanson (2023) and Miranda-Agrippino and Ricco (2021).

This exercise allows us to quantify the potential trade-offs associated with a more aggressive monetary tightening aimed at offsetting the inflationary pressures induced by supply chain disruptions. Specifically, it sheds light on how costly it would be for the central bank to prevent the inflationary impacts of supply chain shocks by responding preemptively and forcefully to signals of supply chain stress.

The results, shown in Figure 13, highlight a key trade-off. A more aggressive monetary response can indeed stabilize prices following a supply chain shock by curbing inflation-

Figure 13: Monetary Policy Counterfactuals



Notes: Responses of industrial production, CPI and the short-term interest rate from our baseline model (black line) against counterfactual responses when monetary policy aims to stabilize prices (dashed red line). The dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

ary pressures through substantial tightening of interest rates. However, this comes at substantial cost: the counterfactual path implies a much sharper contraction in industrial production, falling by almost 1 percent at peak.

Overall, these findings illustrate the complicated trade-offs monetary policy is confronted with in the face of pervasive supply chain pressures.

5. Sectoral Impacts and Substitution

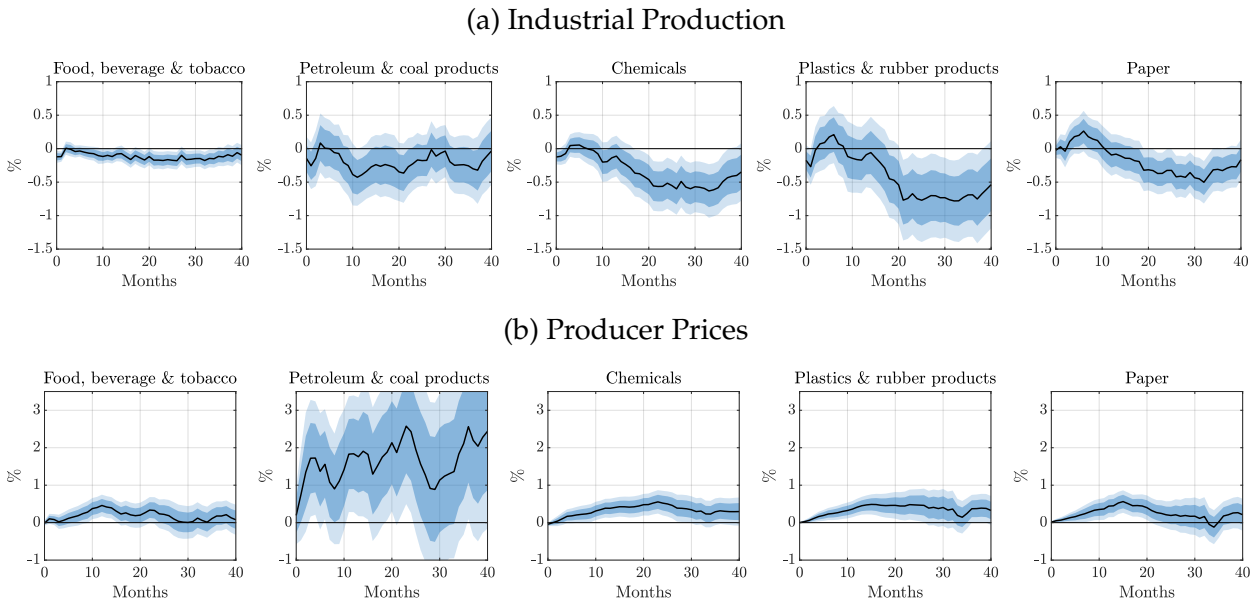
Our reduced-form evidence so far has largely focused on aggregate outcomes. While these effects are informative, they mask potentially important heterogeneity in how supply chain shocks propagate across sectors. This heterogeneity is central for understanding the transmission mechanism and for disciplining quantitative production network models, which rely on assumptions about input linkages and substitution possibilities. In this section, we document how output and prices respond across sectors and use this evidence to inform the degree of substitution across production inputs. We then build on these patterns to formally estimate substitution elasticities, using granular data on inputs sourced as well as input and output prices.

5.1. Sectoral Impacts

To better understand the transmission of supply chain shocks, we examine how their effects differ across sectors. We focus on sectoral responses in industrial production, distinguishing between non-durable and durable goods industries. This disaggregated per-

spective allows us to identify which parts of the production network are most affected by disruptions and how these effects vary across sectors with different input structures. Documenting these patterns provides useful empirical discipline for production network models, which rely on sectoral differences in input linkages and substitution possibilities.

Figure 14: Sectoral Effects: Non-Durable Goods Production



Notes: Impulse responses to a supply chain shock, normalized to increase real shipping costs by 10 percent on impact. The IRFs are estimated by local projections (11) on the aggregated supply chain shock extracted from our baseline external instruments VAR. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

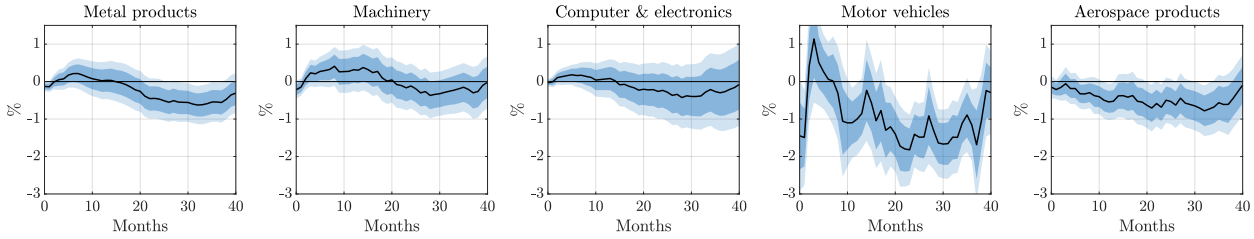
Figures 14 and 15 report impulse responses for industrial production and producer prices across a range of non-durable and durable goods sectors. The effects of the supply chain shock are broad-based but display substantial heterogeneity across industries.

In non-durable goods sectors, quantity responses are heterogeneous but economically meaningful. Production declines are particularly pronounced in industries that rely more heavily on intermediate inputs, such as chemicals and plastics, while other sectors such as food exhibit more muted responses. Price responses also vary substantially across sectors. In particular, upstream industries such as petroleum and coal products display large and persistent increases in producer prices, whereas downstream sectors such as food and paper experience more moderate price pressures. This pattern is consistent with disruptions to key intermediate inputs that propagate along the production chain but are only partially passed through to downstream industries.

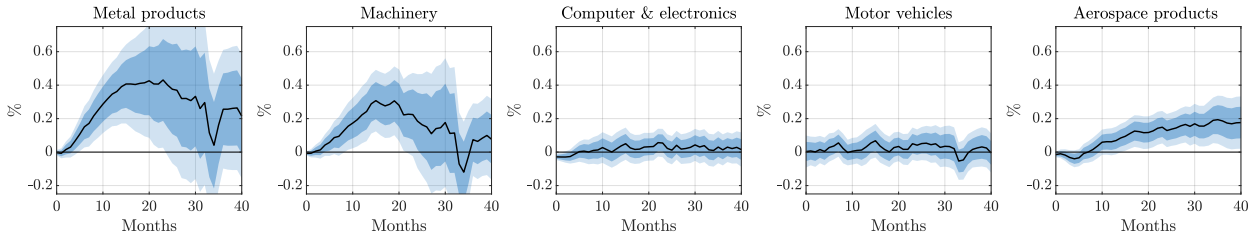
Durable goods sectors display more pronounced heterogeneity in quantity responses.

Figure 15: Sectoral Effects: Durable Goods Production

(a) Industrial Production



(b) Producer Prices



Notes: Impulse responses to a supply chain shock, normalized to increase real shipping costs by 10 percent on impact. The IRFs are estimated by local projections (11) on the aggregated supply chain shock extracted from our baseline external instruments VAR. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

The decline in production is concentrated in specific industries, most notably motor vehicles, with aerospace products also showing a sustained contraction. By contrast, sectors such as machinery and computer and electronic products exhibit more muted responses, although these estimates are imprecise and often not statistically significant. Price responses in durable sectors are generally more moderate, with some increases in upstream segments such as metals, but less pronounced than in non-durable upstream industries.

Taken together, these patterns point to a heterogeneous transmission of supply chain shocks across sectors. Upstream industries experience strong price pressures, while quantity adjustments are concentrated in specific downstream sectors—particularly motor vehicles—and in input-intensive non-durable industries such as chemicals and plastics. These findings highlight the role of production networks in shaping the propagation of supply chain disruptions and motivate the estimation of substitution elasticities across inputs in the next subsection.

5.2. Estimating Substitution Elasticities

The sectoral evidence above points to substantial heterogeneity in how supply chain shocks propagate across industries. This heterogeneity is suggestive of differences in

production structures and, in particular, in the scope for substituting across inputs when relative prices change. Motivated by these patterns, we now formally estimate elasticities of substitution across intermediate inputs. Our goal is to provide empirical discipline for quantitative production network models, which rely on assumptions about how easily firms can reallocate sourcing across suppliers in response to disruptions.

Framework. To guide the empirical specification, we consider a standard multi-sector production network model with a nested constant elasticity of substitution (CES) architecture, following Atalay (2017). Assume the economy consists of N perfectly competitive sectors. Firms in each sector combine capital, labor, and a composite bundle of intermediate inputs to produce gross output. In particular, output in sector i is given by

$$Y_{it} = A_{it}\left[(1-\mu_i)^{\frac{1}{\zeta}} V_{it}^{\frac{\zeta-1}{\zeta}} + \mu_i^{\frac{1}{\zeta}} M_{it}^{\frac{\zeta-1}{\zeta}}\right]^{\frac{\zeta}{\zeta-1}}, \tag{12}$$

where V_{it} is a capital-labor aggregate and M_{it} is a composite of intermediate inputs. The parameter ζ governs substitution between value added and intermediates.

The intermediate input bundle is itself a CES aggregate of inputs sourced from upstream sectors:

$$M_{it} = \left[\sum_{j=1}^{N} \omega_{ij}^{\frac{1}{\eta}} Y_{ijt}^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}, \tag{13}$$

where Y_{ijt} denotes inputs from sector j used by sector i, ω_{ij} captures the baseline importance of supplier j, and η is the elasticity of substitution across intermediate suppliers.

We focus on substitution within the intermediate bundle. Firms choose Y_{ijt} to minimize the cost of assembling M_{it}, taking input prices P_{jt} as given. The first-order condition for this problem implies

$$P_{jt} = P_{it}^{M}\left(\frac{\omega_{ij} M_{it}}{Y_{ijt}}\right)^{\frac{1}{\eta}}, \tag{14}$$

where P_{it}^{M} is the price index of the intermediate bundle. Rearranging yields the conditional demand for input j:

$$Y_{ijt} = \omega_{ij} M_{it}\left(\frac{P_{jt}}{P_{it}^{M}}\right)^{-\eta}. \tag{15}$$

Multiplying by prices and normalizing by total intermediate expenditure gives the

expenditure share

$$s_{ijt}^{M} \equiv \frac{P_{jt} Y_{ijt}}{P_{it}^{M} M_{it}} = \omega_{ij} \left(\frac{P_{jt}}{P_{it}^{M}} \right)^{1-\eta}. \tag{16}$$

Taking logs and first differences eliminates the time-invariant weights ω_{ij} and yields the estimating equation

$$\Delta \ln s_{ijt}^{M} = (1-\eta) \Delta \ln \left(\frac{P_{jt}}{P_{it}^{M}} \right), \tag{17}$$

which relates changes in sourcing shares to changes in relative input prices.

This is our estimating equation. To allow for gradual adjustment, we estimate this relationship dynamically using local projections. Our empirical strategy proceeds in two steps. In the first step, we estimate pair-specific responses of relative prices and expenditure shares to the annualized supply chain shock. In the second step, we relate the estimated quantity responses to the corresponding price responses across industry pairs. This delivers horizon-specific estimates of the elasticity of substitution and allows us to distinguish between short-run and medium-run adjustment.

Data and empirical approach. The estimation requires three ingredients. First, we need time-varying information on intermediate input sourcing across industries to construct expenditure shares s_{ijt}^{M}. Second, we require measures of supplier-level output prices and purchaser-specific intermediate input price indices to form the relevant relative price term. Third, we use our identified supply chain shock, aggregated to the annual frequency. We construct expenditure shares using BEA Make and Use tables and combine these with BEA industry-level gross output deflators to build both output and intermediate input price indices. Appendix A.3 provides full details on the data construction.

We estimate the elasticity of substitution using an annual panel of industry-pair observations spanning 1971 to 2022. For each pair (i, j), where i denotes a purchasing industry and j a supplying industry, we observe the expenditure share s_{ijt}^{M}, the supplier's gross output price P_{jt}, and the purchaser-specific intermediate input price index P_{it}^{M}.

We implement a two-step local projection instrumental variables (LP-IV) approach, which exploits variation in relative input prices induced by the supply chain shock and traces the corresponding adjustment in sourcing patterns.

In the first step, we estimate pair-specific responses of relative prices and expenditure shares to the annualized supply chain shock. For each pair (i, j), we estimate the

contemporaneous response of relative prices:

$$\Delta \ln \left(\frac{P_{jt}}{P_{it}^{M}} \right) = \alpha_{ij}^{P} + \beta_{ij}^{P} SCShock_t + \varepsilon_{ijt}^{P},$$

where β_{ij}^{P} captures how the relative cost of sourcing from supplier j responds to the shock.

We then estimate the response of expenditure shares at horizon h:

$$\ln s_{ij,t+h}^{M} - \ln s_{ij,t-1}^{M} = \alpha_{ij}^{Q}(h) + \beta_{ij}^{Q}(h) SCShock_t + \varepsilon_{ijt}^{Q}(h),$$

where $\beta_{ij}^{Q}(h)$ captures the dynamic adjustment in sourcing from supplier j by purchaser i.

In the second step, we relate the pair-specific quantity responses to the corresponding price responses in a cross-sectional regression:

$$\widehat{\beta ij}^{Q}(h) = \mu_i(h) + \theta(h) \widehat{\beta ij}^{P} + u_{ij}(h),$$

where μ_i are purchasing-industry fixed effects. The inner-nest elasticity of substitution is then recovered as

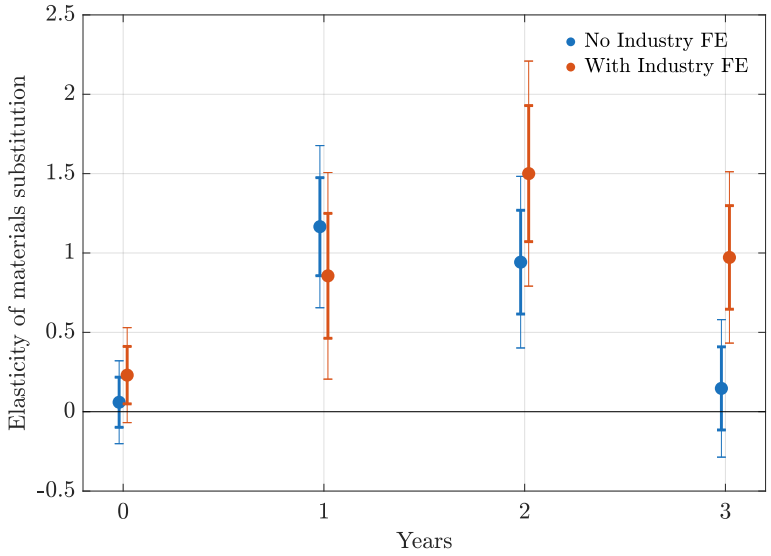
$$\widehat{\eta}(h) = 1 - \widehat{\theta}(h).$$

This procedure isolates variation in relative input prices driven by exogenous supply chain disruptions and maps it into the reallocation of sourcing across suppliers, delivering horizon-specific estimates of substitution elasticities.

Elasticities of substitution. Figure 16 reports the estimated elasticity of substitution across intermediate inputs over the first three years following a supply chain shock. We show results both with and without purchasing-industry fixed effects, which absorb time-invariant differences in production structures across purchasers. The estimates display a clear hump-shaped pattern.

On impact, the estimated elasticity is small and statistically indistinguishable from zero across both specifications, in line with existing estimates in the literature (Atalay, 2017; Miranda-Pinto, 2021). This suggests that firms have little immediate scope to substitute away from a supplier that becomes relatively more expensive following a disruption. Such sluggish short-run adjustment is consistent with procurement rigidities, long-term supplier relationships, and the time required to identify and qualify alternative inputs.

Figure 16: Elasticity of substitution across intermediate inputs



Notes: LP estimates of the inner-nest elasticity $\widehat{\eta}(h) = 1 - \widehat{\theta}(h)$. Blue (red) series excludes (includes) purchasing-industry fixed effects. Shaded bands denote 68 and 90 percent confidence intervals based on heteroskedasticity-robust standard errors.

After the first year, however, the elasticity rises sharply and becomes statistically significant. This indicates that substitution across suppliers takes place only gradually. Firms appear able to reoptimize their sourcing patterns over time as contracts roll over and alternative supply relationships are established. The peak response occurs after roughly one to two years, implying meaningful medium-run substitutability even when short-run substitution is limited.

By the third year, the elasticity declines again, suggesting that most of the adjustment has already taken place. Overall, the results imply that intermediate inputs are difficult to substitute in the short run but become substantially more substitutable at medium horizons. This dynamic pattern is important for quantitative network models, as it implies that the propagation of supply chain shocks depends not only on the static structure of input-output linkages but also on the speed with which firms can reconfigure their sourcing decisions.

6. Conclusion

In this paper, we provide new evidence on the macroeconomic implications of supply chain disruptions, focusing on the critical role of maritime trade choke points. Exploiting plausibly exogenous disruptive events at these bottlenecks and leveraging high-

frequency financial data, we identify structural supply chain shocks and trace their cascading effects on the global economy. Our findings show that disruptive supply chain shocks have pervasive economic effects: they persistently raise shipping costs, commodity prices, and consumer prices, while depressing output and employment. These stagflationary dynamics pose complex challenges for the conduct of monetary policy.

Moving beyond aggregate outcomes, we document substantial heterogeneity in how these shocks propagate across sectors. Upstream industries experience strong price pressures, while output contractions are concentrated in downstream sectors such as motor vehicles and in input-intensive non-durable industries such as chemicals and plastics. Using granular input-output data, we estimate elasticities of substitution across intermediate inputs. We find that substitution is close to zero in the short run, rises to around one after one year, and peaks at about 1.5 after two years, pointing to sluggish but economically meaningful reallocation of sourcing across suppliers.

More broadly, our results highlight the vulnerability of global supply chains and their substantial influence on macroeconomic outcomes. We demonstrate that supply chain shocks contributed meaningfully to the inflationary surge of 2021–22. As climate change, extreme weather, and geopolitical tensions increasingly disrupt global logistics, understanding the role of supply chain shocks will be ever more important for forecasting, policy design, and economic resilience.

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Online Appendix

The Macroeconomic Effects of Supply Chain Shocks: Evidence from Global Shipping Disruptions

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A. Data

A.1. Dataset on Events in Maritime Chokepoints

In this Appendix, we provide additional information on the dataset of events that disrupted shipping traffic in critical maritime chokepoints.

To collect the events, we rely on two sources. First, for both canals, we use newspaper archives accessed through *Dow Jones' Factiva*. While news regarding disruptions are widely reported across mainstream and maritime-specific newspapers, we primarily rely on leading news agencies including Reuters, The Associated Press (AP), and Agence France-Presse (AFP). Second, for the Panama Canal, we also rely on the "Advisory to Shipping" notices issued on the Panama Canal Authority's (ACP) official website: https://pancanal.com/en/maritime-services/advisory-to-shipping/, that include draft restrictions.

Our comprehensive dataset identifies 140 events that disrupted shipping traffic between 1970 and 2022, including 95 events in the Suez Canal and 45 events in the Panama Canal.[1] For each event, we collect detailed information on the reporting of the event, the date of the event, the type of the event, and the severity of the event.

A.2. Macro Data

In Table A.1, we provide information on the macroeconomic data used in the baseline specification, including the data source and sample coverage. The transformed series used in the baseline specification are depicted in Figure A.1.

Table A.1: Data Description and Sources

Variable	Description	Source	Trans.
Instrument			
BDIY	Baltic dry index (daily average), extended using Hamilton (2021)	Bloomberg	$100 \times \Delta \log$
Baseline			
BDIY	Baltic dry index (daily average), extended using Hamilton (2021)	Bloomberg	$100 \times \log$
BCOM	Bloomberg commodity index (daily average)	Bloomberg	$100 \times \log$

Continued on next page

[1] On three specific dates, the Suez Canal and Panama Canal both experienced incidents that disrupted shipping traffic.

Table A.1: Data Description and Sources

Variable	Description	Source	Trans.
TONNAGE	World merchant fleet (thousands of dead-weight tons; weight measure of a vessel's carrying capacity, including cargo, fuel, and stores), extended using Jacks and Stuermer (2021)	UNCTADStat	100 × log
GPRH	Historical geopolitical risk index from Caldara and Iacoviello (2022)	GPR index webpage	100 × log
INDPRO	Industrial production: total index	FRED	100 × log
PCEPI	Personal consumption expenditures: chain-type price index	FRED	100 × log
TB3MS	3-month treasury bill secondary market rate, discount basis	FRED	Level
RNUSBIS	Real narrow effective exchange rate for U.S.	FRED	100 × log
Shipping Rates			
BIDY	Baltic dirty tanker index (daily average), extended using BDIY	Bloomberg	100 × log
BITY	Baltic clean tanker index (daily average), extended using BDIY	Bloomberg	100 × log
HARPEX	Harpex shipping index (weekly average), extended using BDIY	Bloomberg	100 × log
SHSPSCFI	Shanghai export containerized freight index (weekly average), extended using BDIY	Bloomberg	100 × log
WCIDCOMP	Drewry composite container freight benchmark rate (weekly average), extended using BDIY	Bloomberg	100 × log
Additional Monthly Variables			
SHORTAGE	Shortage index from Caldara, Iacoviello, and Yu (2024)	Shortage index webpage	100 × log
FOOD-SHORTAGE	Food shortage index from Caldara, Iacoviello, and Yu (2024)	Shortage index webpage	100 × log
ENERGY-SHORTAGE	Energy shortage index from Caldara, Iacoviello, and Yu (2024)	Shortage index webpage	100 × log
INDUSTRY-SHORTAGE	Industry shortage index from Caldara, Iacoviello, and Yu (2024)	Shortage index webpage	100 × log
LABOR-SHORTAGE	Labor shortage index from Caldara, Iacoviello, and Yu (2024)	Shortage index webpage	100 × log
NAPMSUPL	Supplier delivery times, ISM manufacturing	Bloomberg	100 × log
EPU	Economic policy uncertainty index from Baker, Bloom, and Davis (2016)	Policy Uncertainty webpage	100 × log
TPU	Trade policy uncertainty index from Caldara et al. (2020)	TPU index webpage	100 × log

Continued on next page

Table A.1: Data Description and Sources

Variable	Description	Source	Trans.
OVXCLS	CBOE crude oil ETF volatility index extended using WTISPLC following Bloom (2009)	FRED	100 × log
USTOTPRCF	Terms of trade	Datastream	100 × log
Additional Quarterly Variables			
GDPC1	Real gross domestic product	FRED	100 × log
GPDIC1	Real gross private domestic investment	FRED	100 × log
PCECC96	Personal consumption expenditures	FRED	100 × log
TRADEBAL	Computed using real exports of goods and services (EXPGSC1), real imports of goods and services (IMPGSC1), and GDPC1 as: (EXPGSC1 - IMPGSC1)/GDPC1	FRED	Level
MICH	Median expected price change, 1-year horizon, Surveys of Consumers	FRED	Level
SPF	Median expected change in CPI level, 1-year horizon, Survey of Professional Forecasters	Philadelphia Fed's webpage	Level
Producer Prices			
WPU01PLUS02	Producer price index by commodity: farm products, processed foods and feeds	FRED	100 × log
WPU03T15M05	Producer price index by commodity: industrial commodities less fuels	FRED	100 × log
WTISPLC	Spot crude oil price: West Texas intermediate (WTI)	FRED	100 × log
PCU311311	Producer price index by industry: food manufacturing	FRED	100 × log
PCU312312	Producer price index by industry: beverage and tobacco manufacturing	FRED	100 × log
PCU324324	Producer price index by industry: petroleum and coal products manufacturing	FRED	100 × log
PCU325325	Producer price index by industry: chemical manufacturing	FRED	100 × log
PCU326326	Producer price index by industry: plastics and rubber products manufacturing	FRED	100 × log
PCU322322	Producer price index by industry: paper manufacturing	FRED	100 × log
PCU332332	Producer price index by industry: fabricated metal product manufacturing	FRED	100 × log
PCU333333	Producer price index by industry: machinery manufacturing	FRED	100 × log

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Table A.1: Data Description and Sources

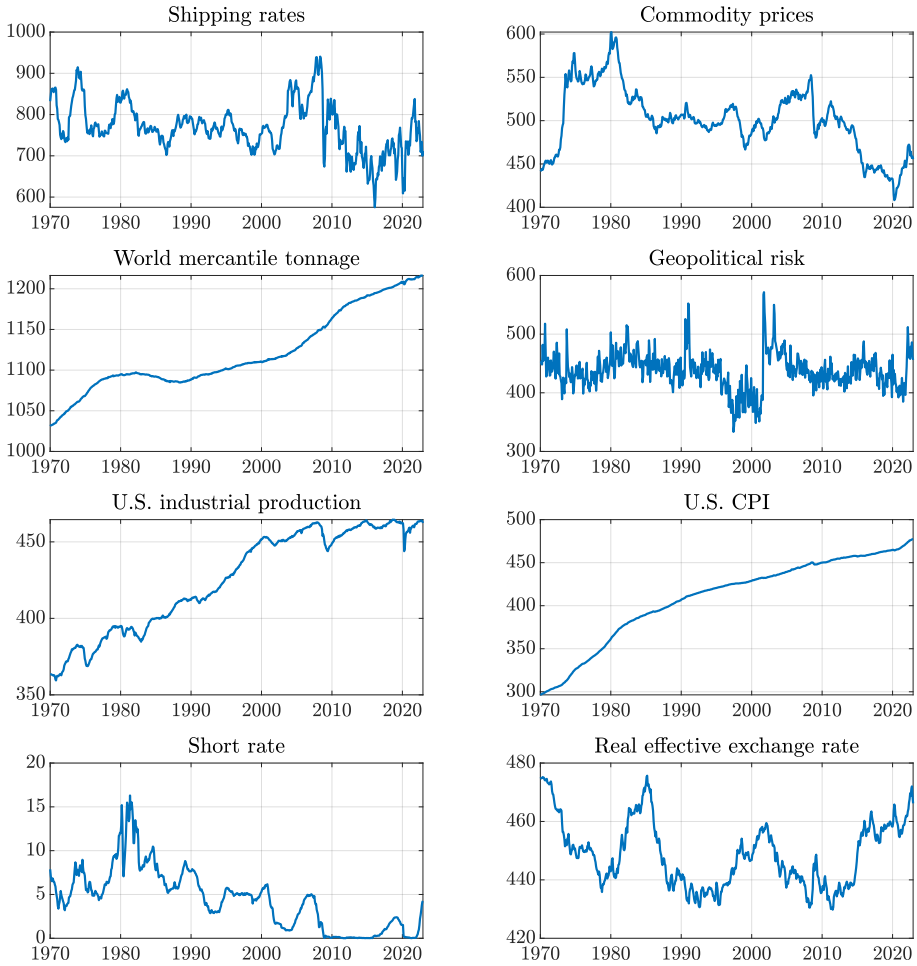
Variable	Description	Source	Trans.
PCU334334	Producer price index by industry: computer and electronic product manufacturing	FRED	$100 \times \log$
PCU33613361	Producer price index by industry: motor vehicle manufacturing	FRED	$100 \times \log$
PCU33623362	Producer price index by industry: motor vehicle body and trailer manufacturing	FRED	$100 \times \log$
PCU33633363	Producer price index by industry: motor vehicle parts manufacturing	FRED	$100 \times \log$
PCU33643364	Producer price index by industry: aerospace product and parts manufacturing	FRED	$100 \times \log$
Industrial Production			
IPFPNSS	Industrial production: final products and nonindustrial supplies	FRED	$100 \times \log$
IPMAT	Industrial production: materials	FRED	$100 \times \log$
IPG311A2S	Industrial production: manufacturing: nondurable goods: food, beverage, and tobacco	FRED	$100 \times \log$
IPG324S	Industrial production: manufacturing: nondurable goods: petroleum and coal products	FRED	$100 \times \log$
IPG325S	Industrial production: manufacturing: nondurable goods: chemical	FRED	$100 \times \log$
IPG326S	Industrial production: manufacturing: nondurable goods: plastics and rubber products	FRED	$100 \times \log$
IPG322S	Industrial production: manufacturing: nondurable goods: paper	FRED	$100 \times \log$
IPG332S	Industrial production: manufacturing: durable goods: fabricated metal product	FRED	$100 \times \log$
IPG333S	Industrial production: manufacturing: durable goods: machinery	FRED	$100 \times \log$
IPG334S	Industrial production: manufacturing: durable goods: computer and electronic product	FRED	$100 \times \log$
IPG3361T3S	Industrial production: manufacturing: durable goods: motor vehicles and parts	FRED	$100 \times \log$
IPG3364T9S	Industrial production: manufacturing: durable goods: aerospace and miscellaneous transportation equipment	FRED	$100 \times \log$
Consumer Prices			
DNDGRG-3M086SBEA	Personal consumption expenditures: nondurable goods (chain-type price index)	FRED	$100 \times \log$

Continued on next page

Table A.1: Data Description and Sources

Variable	Description	Source	Trans.
DNRGRG-3M086SBEA	Personal consumption expenditures: energy goods and services (chain-type price index)	FRED	100 × log
PCEPILFE	Personal consumption expenditures excluding food and energy (chain-type price index)	FRED	100 × log
DDURRG-3M086SBEA	Personal consumption expenditures: durable goods (chain-type price index)	FRED	100 × log
DSERRG-3M086SBEA	Personal consumption expenditures: services (chain-type price index)	FRED	100 × log

Figure A.1: Transformed Data Series



A.3. Sectoral Data

A.3.1. Input-Output Data

Make and Use tables. We rely on the BEA Make and Use tables at the annual frequency from 1970 to 2022. The *Make table* records, for each industry, the dollar value of each commodity it produces. Its rows are industries and its columns are commodities, so the (i, c) entry is the value of commodity c produced by industry i. Because industries often produce secondary commodities alongside their primary commodity output — for example, a steel mill could also sell scrap metal — the Make table is generally not diagonal.

The *Use table* records, for each industry, the dollar value of each commodity it purchases as an intermediate input, as well as its value added. Its rows are commodities and its columns are industries, so the (c, j) entry is the value of commodity c used by industry j. The Use table also includes final demand (consumption, investment, government, and net exports) as additional columns. Together, the Make and Use tables provide a complete account of how commodities flow between producers and users in the economy.

Redefinitions. The BEA publishes each of the above tables in two versions. The *before-redefinitions* tables record each establishment's entire output — primary and secondary commodities alike — under the industry defined by the establishment's primary activity. The *after-redefinitions* tables apply a secondary-product transfer: output of a commodity that is not the primary product of an industry is reassigned ("redefined") to the industry for which that commodity is primary. For example, a hotel that operates an on-site restaurant generates food and beverage revenue as a secondary product alongside its primary accommodation output. In the before-redefinitions table, revenue from both accommodation and food services is recorded under the accommodation industry. In the after-redefinitions table, the food and beverage portion is transferred to the food services industry, for which it is the primary product.

We use before-redefinitions tables for two reasons. First, consistency: the redefinitions change over time, so a before-redefinitions panel maintains a stable commodity classification from 1970 to 2022. Second, alignment with our price data: we rely on BEA industry-level gross output price deflators, which are constructed on an establishment basis and therefore better align with the before-redefinition concept of industry output (Horowitz and Planting, 2009, p. 4–5).

Producer vs. purchaser prices. The Use tables are published in two valuations: at producer prices, which record what the seller receives, and at purchaser prices, which add

wholesale and retail trade margins and transport costs to obtain what the buyer pays. We use the producer-price version throughout, as this is the only valuation available for the historical 1970 to 1996 tables.

Industry coverage. The 1970–1996 tables are defined over 65 industries; the 1997–2022 tables over 71. We harmonize the post-1997 tables to the 65-industry classification using the standard consolidations: retail trade subcategories `441`, `445`, `452`, and `4A0` to `44RT`; real estate subcategories `HS` and `ORE` to `531`; hospitals, `622`, and nursing and residential care facilities, `623`, to `622HO`; federal general government defense, `GFGD`, and non-defense, `GFGN`, to `GFG`. Next, following Atalay (2017), we further aggregate the BEA summary-level industries, as defined in Table A.2.

Notation. Let V denote the $N \times N$ Make matrix (industries $\times$ commodities), U the $N \times N$ intermediate portion (i.e., excluding final demand columns and value-added rows) of the Use matrix (commodities $\times$ industries), q the $N \times 1$ vector of total commodity output, and g the $N \times 1$ vector of total industry output.

A.3.2. Construction of Expenditure Shares

Our object of interest is the nominal expenditure share s^M_{ijt}: the fraction of industry i's total intermediate goods expenditure allocated to inputs sourced from industry j in year t. Because BEA tables record commodity flows rather than industry-to-industry flows, we follow Horowitz and Planting (2009), p. 12-21 to redistribute commodity purchases back to their producing industries. The construction proceeds in three steps.

Step 1: Market shares. Define the market-share matrix as:

$$D = V\hat{q}^{-1},$$

where $\hat{q}$ is the diagonal matrix with total commodity output q on the diagonal. The (i, c) entry $D_{ic} = V_{ic}/q_c$ is the share of commodity c's output produced by industry i. Each column of D sums to one.

Step 2: Industry-by-industry nominal use. Pre-multiplying the Use matrix by D converts commodity-based flows into industry-to-industry flows:

$$\widetilde{U} = D\,U. \tag{1}$$

Table A.2: Aggregation of BEA Summary-Level Industries

Sector	BEA Summary Codes
Agriculture & Forestry	111CA, 113FF
Oil & Gas Extraction	211, 213
Mining	212
Utilities	22
Construction	23
Food & Kindred Products	311FT
Textile Mills	313TT
Apparel & Leather Products	315AL
Wood Products	321
Paper & Allied Products	322
Printing & Publishing	323, 511
Petroleum & Coal Products	324
Chemical Products	325
Plastics & Rubber Products	326
Non-Metallic Mineral Products	327
Primary Metals	331
Fabricated Metal Products	332
Machinery	333
Computer & Electronic Products	334
Electrical Equipment	335
Motor Vehicles	3361MV
Other Transport Equipment	3364OT
Furniture	337
Misc. Manufacturing	339
Wholesale & Retail Trade	42, 44RT
Transportation & Warehousing	481, 482, 483, 484, 485, 486, 487OS, 493
Communications	512, 513, 514
FIRE	521CI, 523, 524, 525, 531, 532RL
Other Services	5411, 5412OP, 5415, 55, 561, 562, 61, 621, 622HO, 624, 711AS, 713, 721, 722, 81
Government	GFG, GFE, GSLG, GSLE

Notes: Aggregation follows Atalay (2017), Table 7. Codes are BEA summary-level industry codes from the Input-Output Accounts. 44RT consolidates retail trade sub-categories (441, 445, 452, 4A0); 531 consolidates housing services and other real estate (HS, ORE); 622HO consolidates hospitals and nursing/residential care (622, 623); GFG consolidates federal general government defense and nondefense (GFGN, GFGD).

The (i, j) entry $\sum_c D_{ic} U_{cj}$ is the total dollar value of purchases by industry j attributable to producing industry i.

Step 3: Expenditure shares. Finally, we normalize each column of $\widetilde{U}$ by total intermediate spending to obtain expenditure shares:

$$s_{ijt}^{M} = \frac{\tilde{U}_{ji}}{\sum_{k} \tilde{U}_{ki}}. \tag{2}$$

Each column sums to one by construction.

Numerical illustration. We illustrate each step using the sample Make and Use tables from Horowitz and Planting (2009), Chapter 12.
The Make table (V), with total industry output in the final column, is:

Table A.3: Make Table

	Commodity				
Industry	A	B	C	Scrap	Total industry output
A	300	25	0	3	328
B	30	360	20	2	412
C	0	15	250	0	265
Total commodity output	330	400	270	5	

The Use table, including value added and final demand, is:
The intermediate block U consists of the first three commodity rows and the three industry columns (excluding the scrap row, value added, and final demand).[2]

Step 1. Dividing each column of the Make table V (excluding the scrap column) by total commodity output q gives the market-share matrix D:
For instance, industry A produces 90.9% of all commodity A output and 6.3% of commodity B output.

[2]In practice, when computing our baseline expenditure shares, we include scrap as an intermediate input commodity. This is to ensure consistency with the latest available BEA methodology for industry-by-industry total requirements tables, which are constructed from the complete Use matrix, including scrap rows. In practice, scrap purchases are small relative to total intermediate spending for most industries, and our results are insensitive to this choice.

Table A.4: Use Table

	Industry				
Commodity	A	B	C	Final demand	Total commodity output
A	50	120	120	40	330
B	180	30	60	130	400
C	50	150	50	20	270
Scrap	1	3	1	0	5
Value added	47	109	34		190
Total industry output	328	412	265	190	

Table A.5: Market Shares Matrix

	Commodity		
Industry	A	B	C
A	$300/330 = 0.909$	$25/400 = 0.063$	$0/270 = 0.000$
B	$30/330 = 0.091$	$360/400 = 0.900$	$20/270 = 0.074$
C	$0/330 = 0.000$	$15/400 = 0.038$	$250/270 = 0.926$
Total commodity output	1.000	1.000	1.000

Step 2. Pre-multiplying U by D converts commodity-by-industry flows into industry-by-industry flows. For example:

$$\widetilde{U}_{AA} = (0.909 \times 50) + (0.0625 \times 180) + (0.000 \times 50) = 56.70.$$

Computing all nine entries gives the full industry-by-industry nominal use matrix $\widetilde{U}$:

Table A.6: Industry-by-Industry Use Table

	Purchasing Industry		
Supplying Industry	A	B	C
A	56.70	110.97	112.84
B	170.25	49.02	68.61
C	53.05	140.01	48.55
Total intermediate spending	280.00	300.00	230.00

Step 3. Dividing each column by its total yields the expenditure shares:

Table A.7: Industry-by-Industry Intermediate Expenditure Shares

	Purchasing Industry		
Supplying Industry	A	B	C
A	$56.70/280 = 0.203$	$110.97/300 = 0.370$	$112.84/230 = 0.491$
B	$170.25/280 = 0.608$	$49.02/300 = 0.163$	$68.61/230 = 0.298$
C	$53.05/280 = 0.189$	$140.01/300 = 0.467$	$48.55/230 = 0.211$
Column sum	1.000	1.000	1.000

Each entry (i, j) is the share of industry j's total intermediate budget allocated to supplier i. For instance, industry A allocates 60.8% of its intermediate budget to inputs from industry B and 20.3% to inputs from industry A itself. These shares form the time-varying weights entering our estimating equation (**??**).

A.3.3. Price Data

Source. We construct annual output and intermediate input price indices drawing on the BEA *GDP by Industry* accounts. We use the chain-type price indices for gross output

for the period 1970 to 2022.[3] We also rely on nominal gross output values for constructing aggregation weights over the same period.

Splicing modern and historical series. The modern (1997 to 2022) and historical (1970 to 1997) price indices share a common year at 1997. We thus splice the two series by rebasing the historical index onto the modern scale at 1997. Thus, for each industry j, we multiply each historical observation by the ratio of the modern to historical index value in 1997,

$$\widetilde{P}_{jt} = P_{jt}^{\text{hist}} \times \frac{P_{j,1997}^{\text{modern}}}{P_{j,1997}^{\text{hist}}}, \qquad t < 1997,$$

so that the spliced series is expressed in the same units as the modern data throughout (with a base year of 2017).

A.3.4. Construction of Output and Intermediate Input Price Indices

Gross output price indices. The price indices for the 65 BEA summary-level industries are aggregated to the broader sectors using a Törnqvist price index following Atalay (2017). For each sector i and adjacent years $t-1$ and t, the log change in the price index is:

$$\Delta \log P_{i,t} = \sum_{j \in S} \overline{w}_{j,t} \, \Delta \log P_{j,t},$$

where S denotes summary-level industries part of the broader sector i and the Törnqvist weight is the average nominal gross output share across the two years,

$$\overline{w}_{j,t} = \frac{1}{2}\left(s_{j,t-1} + s_{j,t}\right), \qquad s_{j,t} = \frac{\text{Output}_{j,t}}{\sum_{k \in S} \text{Output}_{k,t}}.$$

Log changes are chained from 1970 to 2022, and the resulting log-level index is rebased so that each sector's price equals 100 in 2017.

[3] The combined hospital and nursing care industry (622HO) is reported as two separate lines in the modern files—Hospitals (line 78) and Nursing and Residential Care Facilities (line 79)—but as a single combined line 78 in the historical files. For the modern period, we construct a single 622HO price index by using the Törnqvist aggregation. For the historical period, line 78 is used directly.

Intermediate input price indices. For each sector i and adjacent years $t-1$ and t, the log change in the intermediate input price index is:

$$\Delta \log P_{i,t}^{M} = \sum_{j=1}^{30} \overline{w}_{ij,t}^{M} \Delta \log P_{j,t},$$

where $P_{j,t}$ is the gross output price index for supplier sector j and the Törnqvist weight is the average intermediate input expenditure share across adjacent years,

$$\overline{w}_{ij,t}^{M} = \frac{1}{2}\left(s_{ij,t-1}^{M} + s_{ij,t}^{M}\right).$$

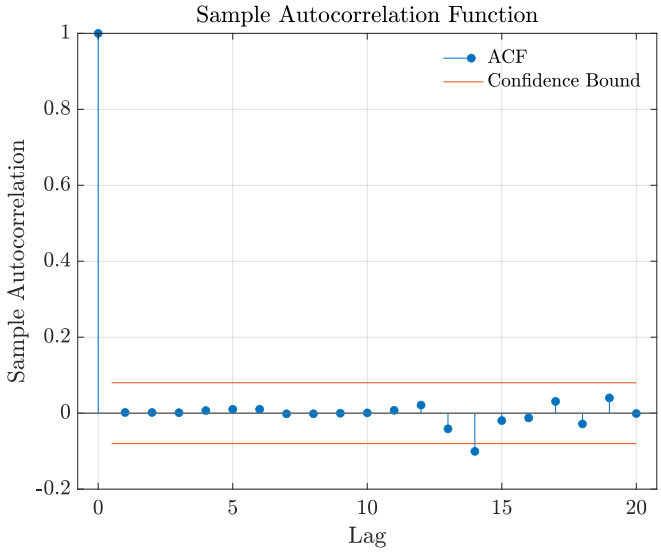
The expenditure shares $s_{ij,t}^{M}$ are constructed as described in Equation 2. The log changes are chained and the resulting index is rebased to 2017.

B. Diagnostics of the Surprise Series

As discussed in the paper, we perform a number of additional checks to ascertain the validity of the surprise series. In this section, we investigate the autocorrelation and forecastability of the surprise series, as well as its correlation with other shocks from the literature.

Autocorrelation. In Figure B.1, we present the autocorrelation function. We find no evidence that the surprise series is serially correlated. The p-value for the Q-statistic that all autocorrelations are zero is 0.99.

Figure B.1: Autocorrelation Function



Granger causality tests. In Table B.1, we present the results of a number of Granger causality tests. We find little evidence that macroeconomic or financial variables have any power in forecasting the surprise series. For all variables considered, the p-values for the Granger causality test are far above conventional significance levels, with the joint test having a p-value of 0.83. The only exception is shipping rates, which individually helps predict the surprises somewhat. However, removing this predictability by purging our surprises by shipping rates yields very similar results.

Table B.1: Granger Causality Tests

Variable	p-value
Instrument	0.9906
Shipping rates	0.2474
Commodity prices	0.8855
World mercantile tonnage	0.8975
Geopolitical risk	0.7192
U.S. industrial production	0.5380
U.S. CPI	0.5932
Short rate	0.9182
Real effective exchange rate	0.5079
Oil price	0.6678
Shortage index	0.6106
Joint	0.8571

Notes: This table shows the p-values of a series of Granger causality tests of the shipping costs surprise series using a selection of macroeconomic and financial variables. To be able to conduct standard inference, the series are made stationary by taking first differences where necessary. The lag order is set to 6 and in terms of deterministics, only a constant term is included.

Correlation with other shock measures. Finally, in Table B.2 we examine how the shipping costs surprise series correlated with other shocks from the literature. The surprise series is uncorrelated with other structural shock measures from the literature, including oil, productivity, news, monetary policy, uncertainty, financial, and fiscal policy shocks.

Table B.2: Correlation with Other Shock Measures

Shock	Source	ρ	p-value	n	Sample
Panel A: Oil shocks					
Oil price	Hamilton, 2003	0.03	0.56	396	1985M01-2017M12
Oil supply	Kilian, 2008	-0.10	0.12	237	1985M01-2004M09
	Caldara, Cavallo, and Iacoviello, 2019	-0.06	0.29	372	1985M01-2015M12
	Baumeister and Hamilton, 2019	0.00	0.95	456	1985M01-2022M12
	Kilian, 2009	-0.08	0.17	276	1985M01-2007M12
Global demand		0.10	0.11	276	1985M01-2007M12
Oil-specific demand		-0.03	0.60	276	1985M01-2007M12
Oil supply news	Känzig, 2021	-0.01	0.83	456	1985M01-2022M12
Panel B: Productivity Shocks					
Productivity	Basu, Fernald, and Kimball, 2006	-0.04	0.71	108	1985Q1-2011Q4
	Smets and Wouters, 2007	-0.05	0.63	80	1985Q1-2004Q4
Panel C: News shocks					
News	Barsky and Sims, 2011	-0.20	0.06	91	1985Q1-2007Q3
	Kurmann and Otrok, 2013	0.15	0.19	82	1985Q1-2005Q2
	Beaudry and Portier, 2014	0.01	0.90	111	1985Q1-2012Q3
Panel D: Monetary policy					
Monetary policy	Bauer and Swanson, 2023	0.01	0.89	383	1988M02-2019M12
	Gertler and Karadi, 2015	0.01	0.87	324	1990M01-2016M12
	Romer and Romer, 2004	-0.01	0.94	144	1985M01-1996M12
	Smets and Wouters, 2007	-0.09	0.45	80	1985Q1-2004Q4
Panel E: Uncertainty shocks					
Uncertainty	Bloom, 2009	-0.04	0.39	396	1985M01-2017M12
	Baker, Bloom, and Davis, 2016	-0.05	0.30	390	1985M07-2017M12
Panel F: Financial shocks					
Financial	Gilchrist and Zakrajšek, 2012	-0.04	0.48	372	1985M01-2015M12
	Bassett et al., 2014	-0.08	0.48	76	1992Q1-2010Q4
Panel G: Fiscal policy shocks					
Fiscal policy	Romer and Romer, 2010	-0.15	0.17	92	1985Q1-2007Q4
	Ramey, 2011	-0.08	0.41	104	1985Q1-2010Q4
	Fisher and Peters, 2010	0.00	0.97	96	1985Q1-2008Q4

Notes: This table shows the correlation of the shipping cost surprise series with a wide range of structural shock measures from the literature. ρ is the Pearson correlation coefficient, the p-value corresponds to the test whether the correlation is different from zero, and n is the sample size. When the shock measure is only available at the quarterly frequency, the surprise series is aggregated by summing across months.

C. Sensitivity Analysis

C.1. Instrument Construction

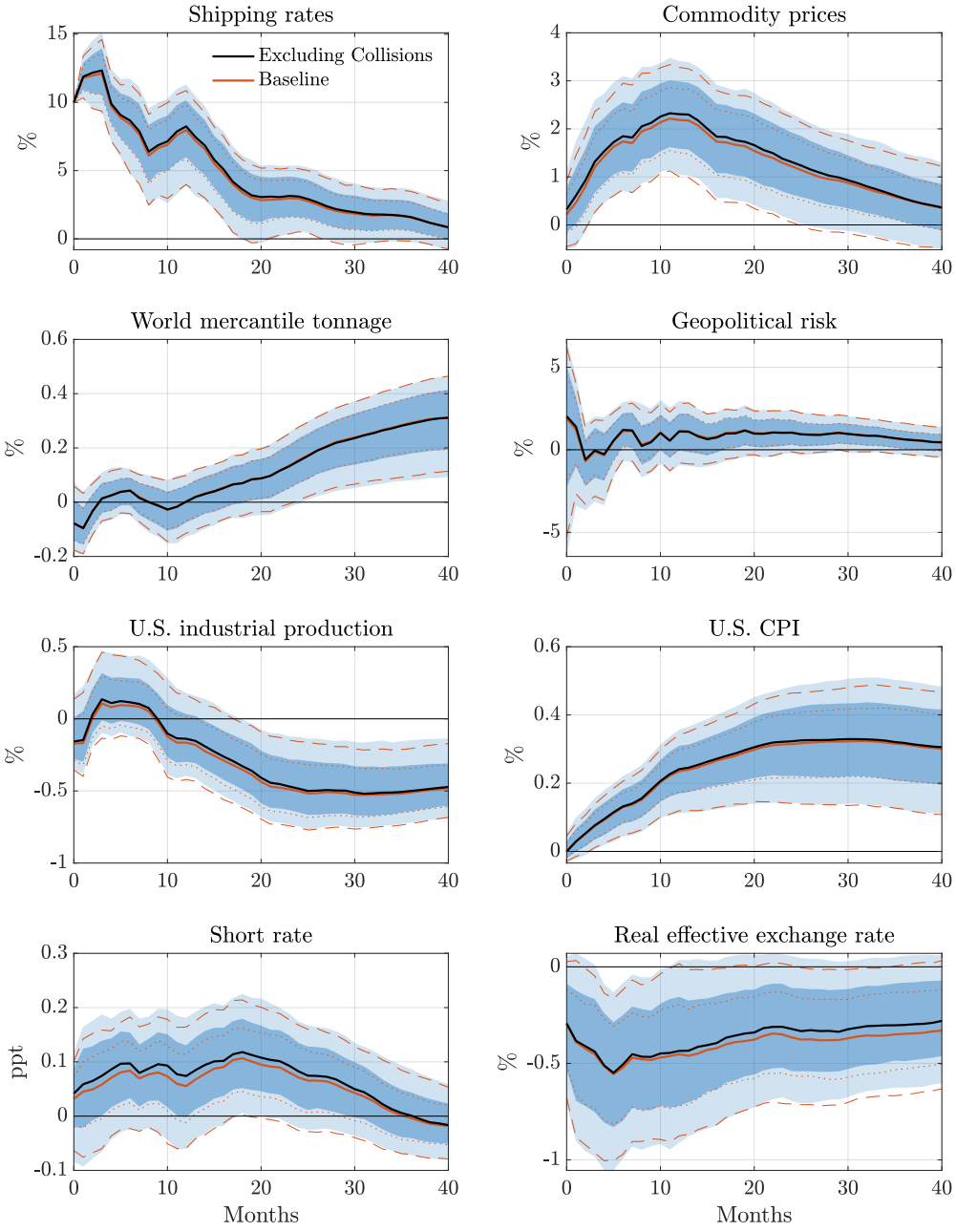
Event selection. A potential concern with our baseline instrument is that vessel collisions at maritime choke points may be more likely to occur during periods of heightened shipping activity, which could itself be correlated with broader macroeconomic conditions. To assess whether inclusion of collisions introduces any endogenous variation into our instrument, we re-estimate the responses using a version of the surprise series that excludes all collision-related events from the narrative dataset. As shown in Figure C.1, the impulse responses are virtually unchanged relative to the baseline, indicating that our results are not driven by the subset of events for which endogeneity concerns are most acute.

To additionally verify that no single event exerts undue influence on our estimates, we conduct a jackknife exercise in which we censor each observation in our surprise series to zero, one at a time, and re-estimate the baseline model for each resulting instrument. Figure C.2 shows the collection of responses using the modified instrument (in gray), along with the baseline response (in black). The results do not appear to be driven by any individual event, as the resulting responses lie safely within the 68 percent confidence interval of the baseline model.

Predictability. Next, we explore how potential predictability of our events affects the results. A potential concern is that some disruptions may be at least partially anticipated. For instance, at the Panama Canal, draft restrictions imposed in response to adverse weather conditions may be anticipated as market participants may foresee the likelihood of further restrictions following an initial one. To address this, we construct a more restrictive instrument that retains only the first draft restriction in each sequence of related Panama Canal events, discarding subsequent restrictions that are arguably more predictable. As shown in Figure C.3, the impulse responses are very similar to the baseline, suggesting that anticipatory effects associated with repeated restrictions do not materially bias our estimates.

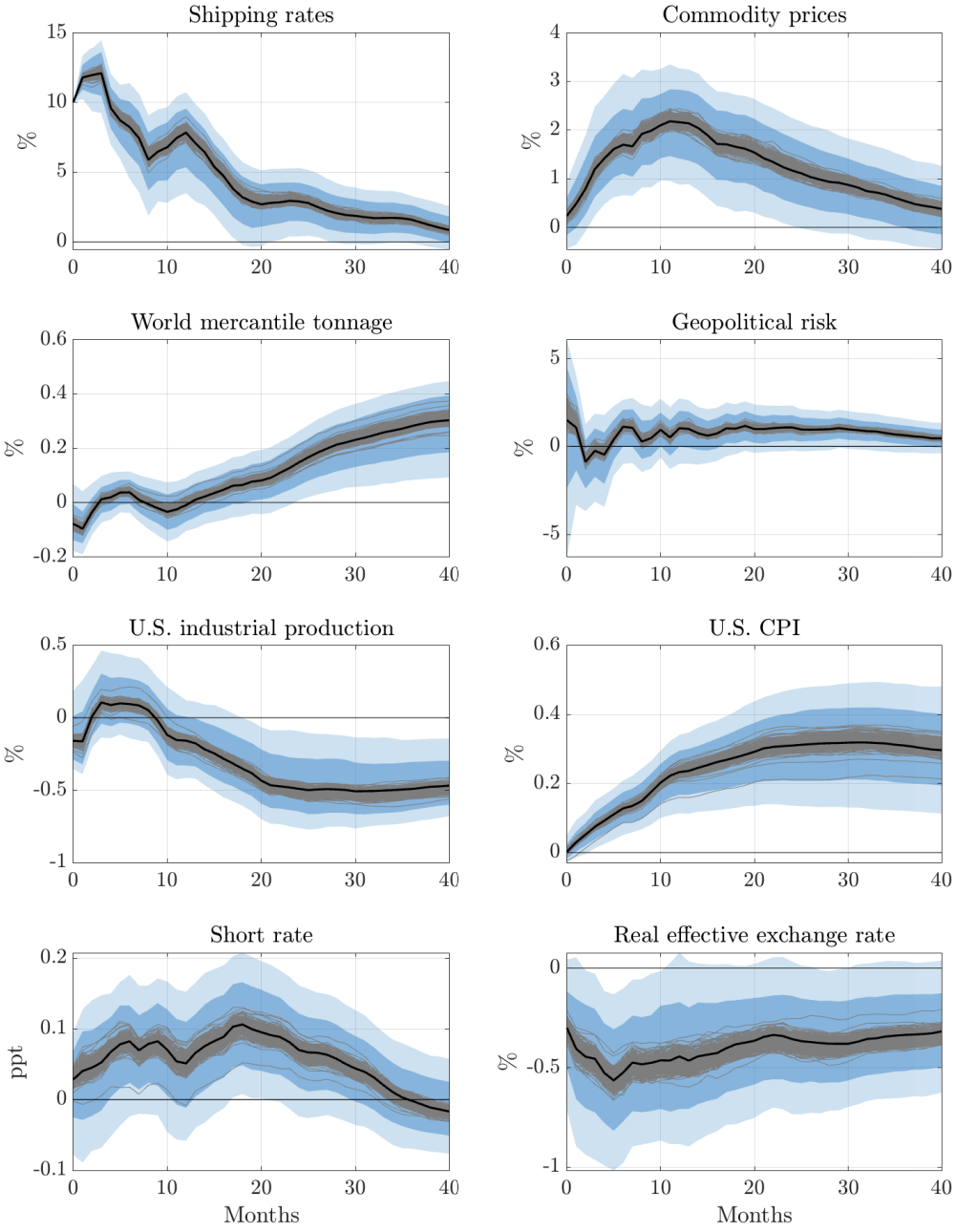
As a complementary check, Figure C.4 shows the impulse responses using the raw surprise series, forgoing any attempt to remove predictability altogether. The results are virtually identical to the baseline, indicating that the predictability correction has little bearing on our estimates.

Figure C.1: Sensitivity With Respect to Excluding Collisions



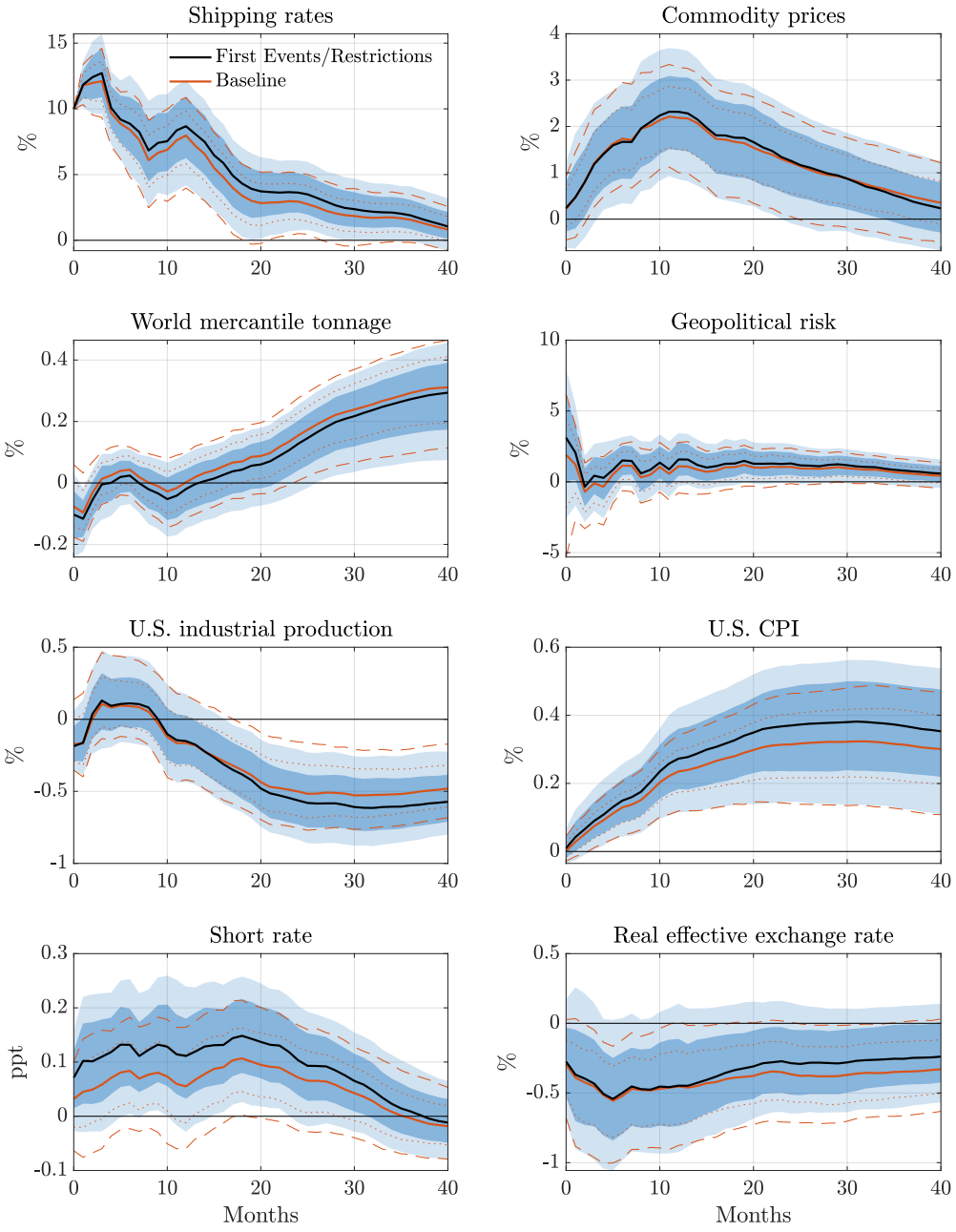
Notes: Impulse responses to a supply chain shock using an instrument that excludes collisions. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.2: Jackknife Exercise



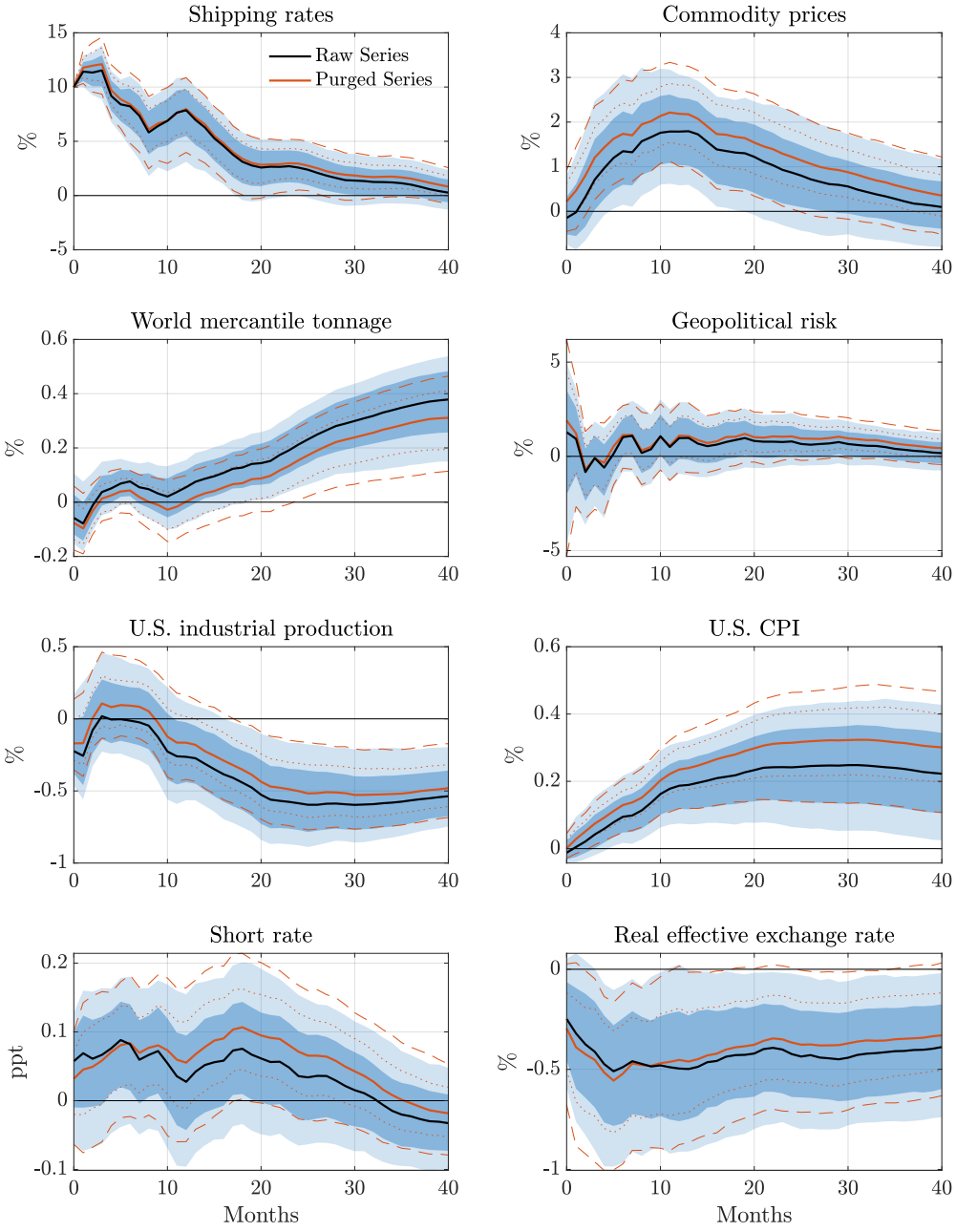
Notes: Impulse responses to a supply chain shock from the jackknife exercise. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.3: Sensitivity With Respect to Event Selection



Notes: Impulse responses to a supply chain shock using an instrument that relies on a more restrictive set of events or draft restrictions. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.4: Raw Surprises



Notes: Impulse responses to a supply chain shock using the raw instrument. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Event window. In our baseline, we measure shipping cost surprises using a one-day event window. To assess the sensitivity of our results to this choice, we re-estimate the model using surprises computed over a two-day and a five-day event window, which allow for the possibility that markets take longer to fully process certain disruptions. As shown in Figure C.5, the impulse responses under both alternative windows are essentially identical to the baseline, alleviating concerns that the length of the event window materially affects our estimates.

Canals. A further concern is that disruptions in the Suez Canal may coincide with major geopolitical developments in the Middle East, raising the possibility that our instrument captures variation unrelated to supply chain conditions. While our baseline specification already controls for a news-based geopolitical risk index, we assess this more directly by re-estimating the model using instruments based on events in each canal separately. As shown in Figure C.6, the responses using only Panama Canal events are very similar to the baseline, alleviating concerns that geopolitical confounders are driving our results. The one exception is the real effective exchange rate, which increases rather than decreases, potentially reflecting the different composition of trade flows and commodities, particularly energy, that pass through the two canals.

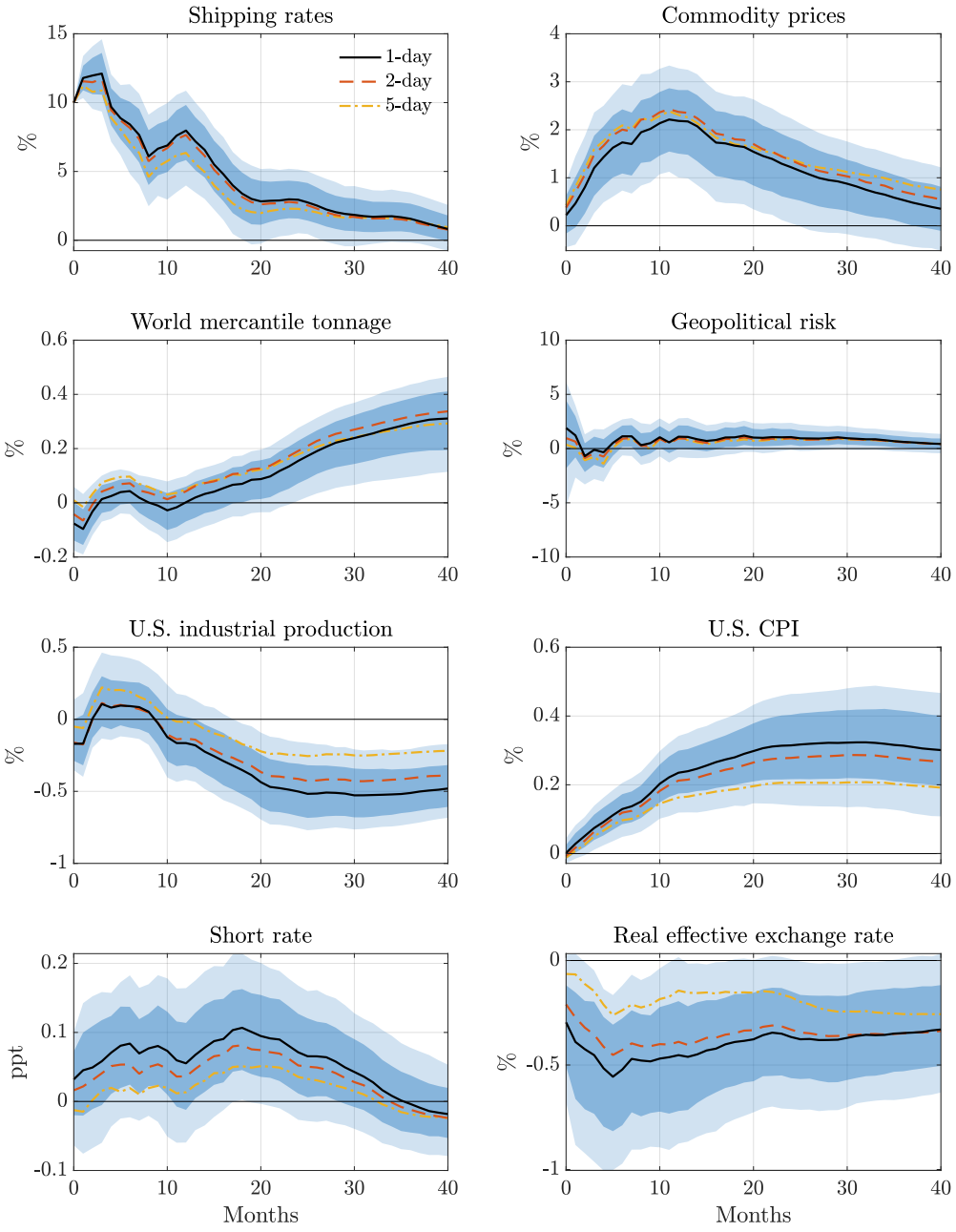
Negative surprises. A potential concern is that negative surprises in shipping costs may coincide with adverse macroeconomic news, confounding their interpretation as exogenous supply chain shocks. To mitigate this concern, we show that our baseline results are robust to keeping only positive shipping disruptions, censoring negative surprises to zero. As shown in Figure C.7, the impulse responses are very similar to the baseline, alleviating concerns that negative surprises introduce spurious variation into the instrument.

C.2. Sample and Specification Choices

Sample. We assess the sensitivity of our results to the sample period. A first concern is that the oil price shocks of the 1970s may confound our estimates, given their outsized influence on global commodity markets and shipping activity. Figure C.8 presents responses based on a sample excluding the 1970s, and shows that our results are robust to this restriction, though the price responses are slightly more muted.

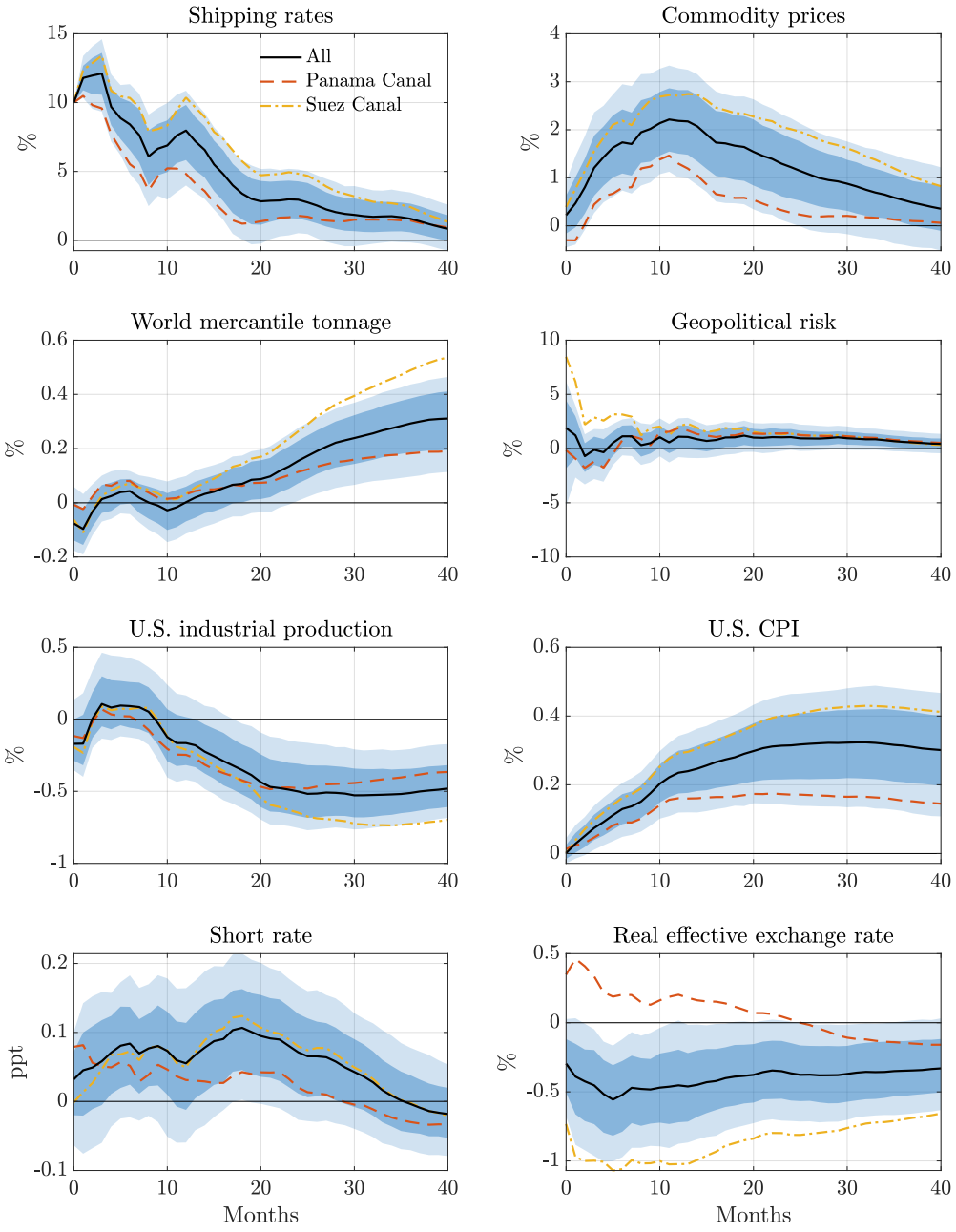
A second concern is that the Covid-19 pandemic generated unprecedented disruptions to global supply chains that may be difficult to separate from the shipping disruptions captured by our instrument. Figure C.9 presents responses based on a sample excluding

Figure C.5: Sensitivity With Respect to Event Window



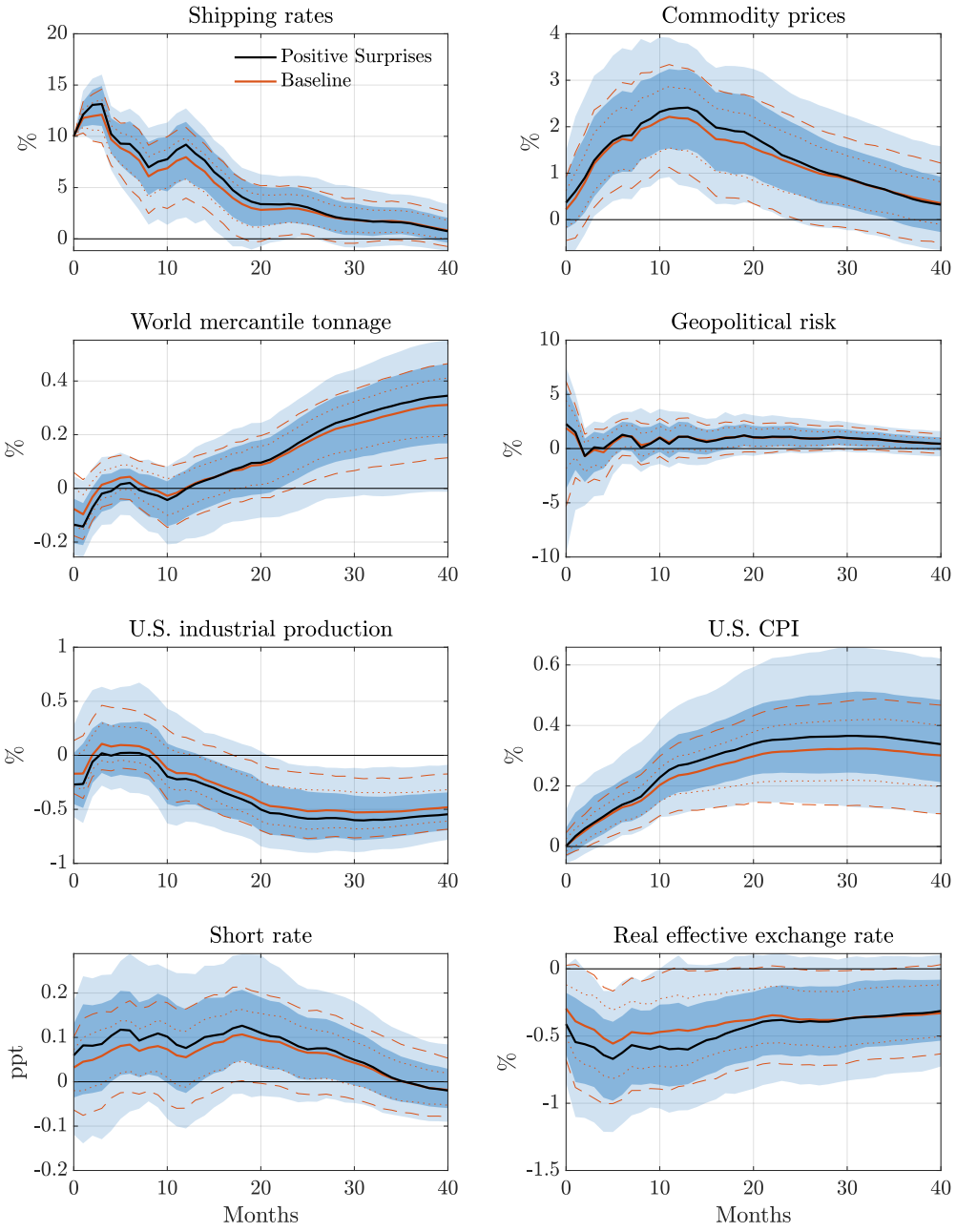
Notes: Impulse responses to a supply chain shock using an instrument with surprises computed over a longer event window. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.6: Sensitivity With Respect to Canals



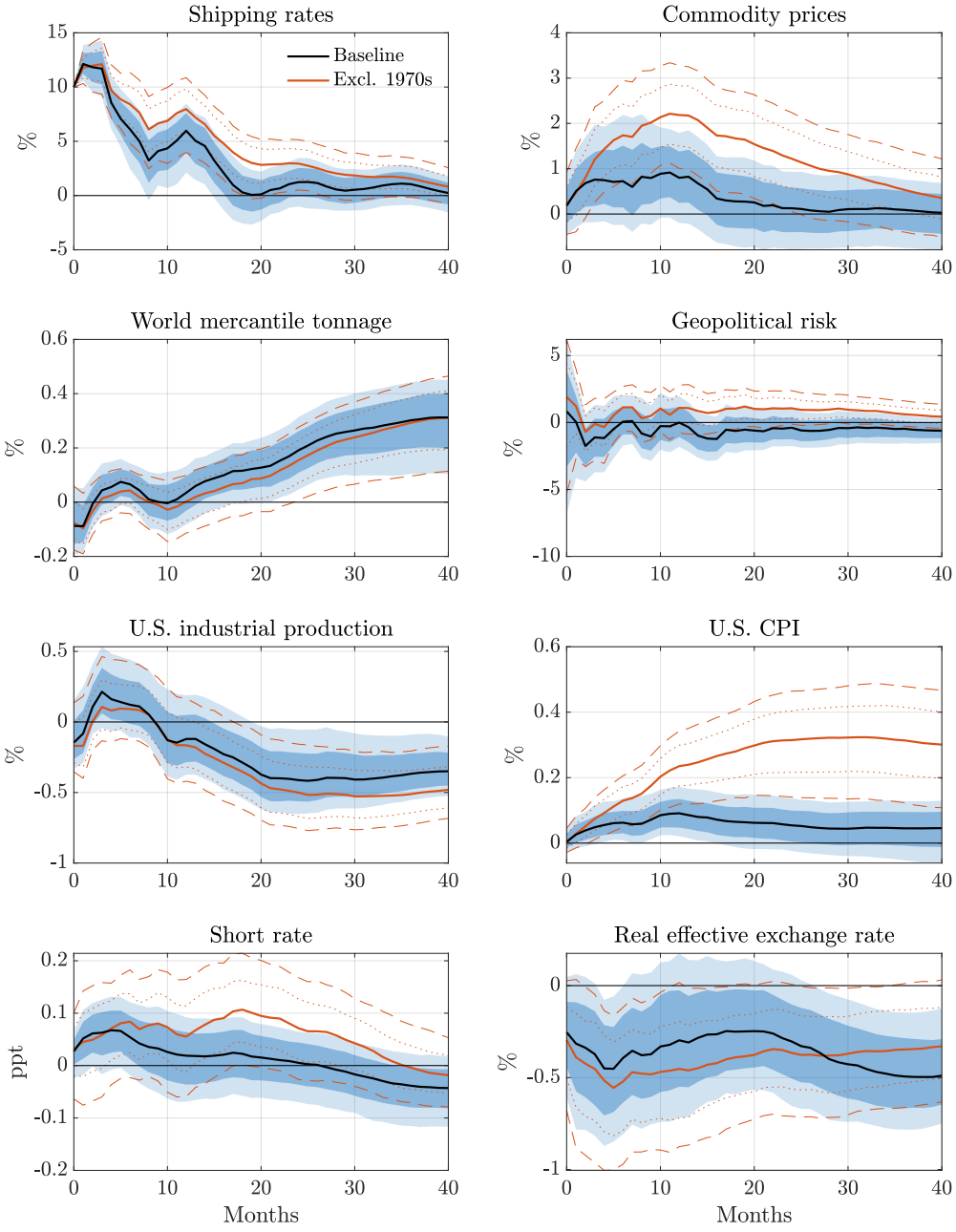
Notes: Impulse responses to a supply chain shock using an instrument that includes events in the Panama canal or in the Suez canal alone. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.7: Sensitivity With Respect to Negative Surprises



Notes: Impulse responses to a supply chain shock using an instrument that censors negative surprises to zero. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.8: Excluding the 1970s



Notes: Impulse responses to a supply chain shock based on a sample excluding the 1970s. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

the Covid-19 period, and again confirms that our baseline results are not driven by this episode.

Lag order. We assess the sensitivity of our results to the choice of lag order. Our baseline specification sets the lag order to 12, as is customary with monthly data. Figure C.10 shows the impulse responses under alternative lag orders of 6 and 18. The responses are essentially identical across all three specifications, indicating that our results are not sensitive to the number of lags included in the VAR.

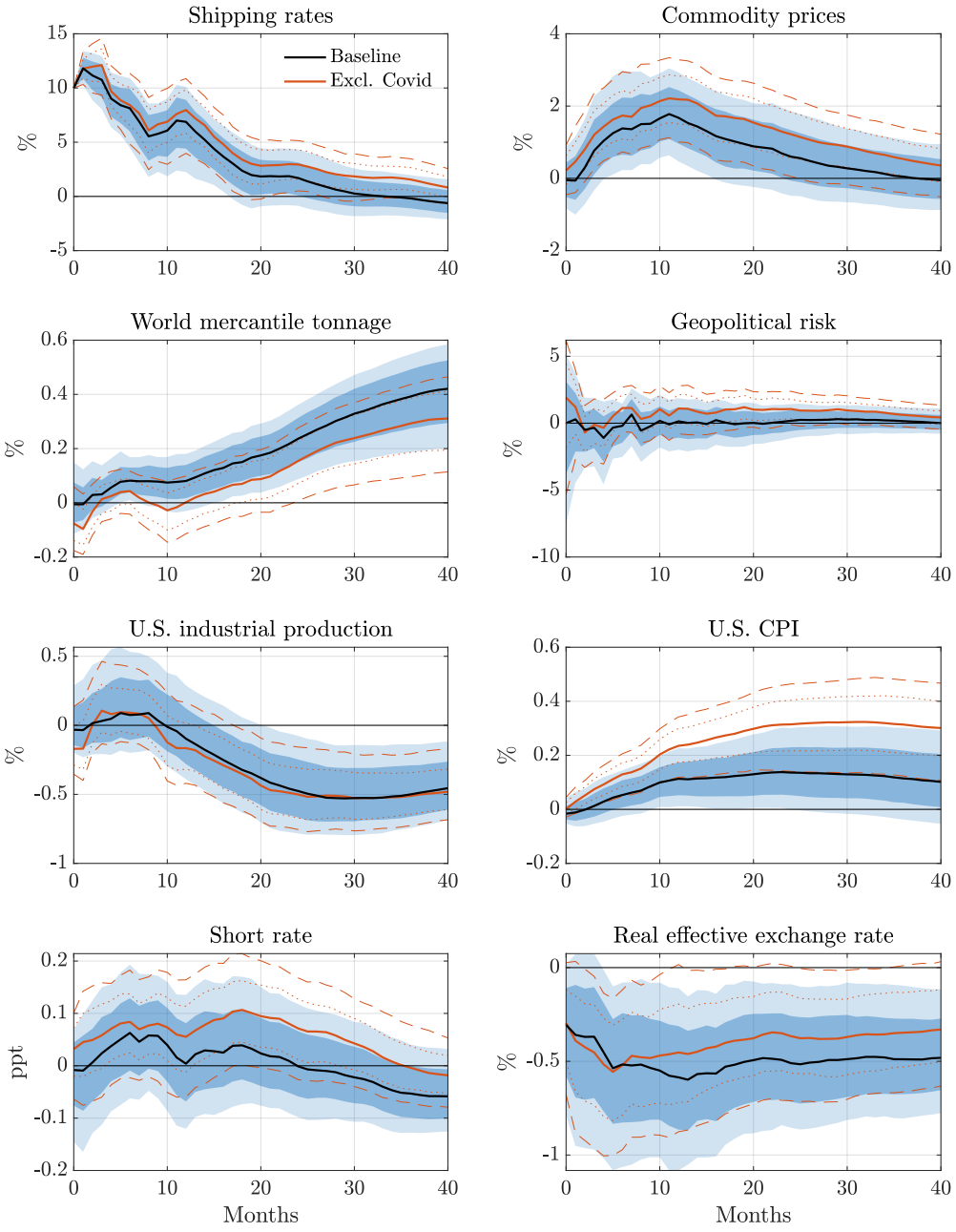
Deterministics. We also assess the sensitivity of our results to the choice of deterministic terms. Our baseline specification includes a linear trend. Figure C.11 shows the impulse responses when the linear trend is omitted and when we additionally control for the global financial crisis and the Covid-19 period using dummy variables. The responses are essentially identical to the baseline across all specifications, indicating that our results are not driven by the particular choice of deterministic terms.

D. Additional Results

Shortages. To corroborate our interpretation of a supply chain shock, we study the effects of the shock on a range of shortage measures constructed by Caldara, Iacoviello, and Yu (2024)). Figure 8a shows the responses of the components of the shortage index. The results are consistent with our interpretation of a supply chain shock. Energy and industrial material shortages increase significantly following the shock, reflecting the disruption to the transport of key inputs along global shipping routes. Labor shortages also increase, though the response is more muted, suggesting secondary propagation through production bottlenecks. Food shortages, by contrast, show little response, which is perhaps unsurprising given that food supply chains rely more heavily on domestic sourcing and are less exposed to disruptions at maritime choke points.

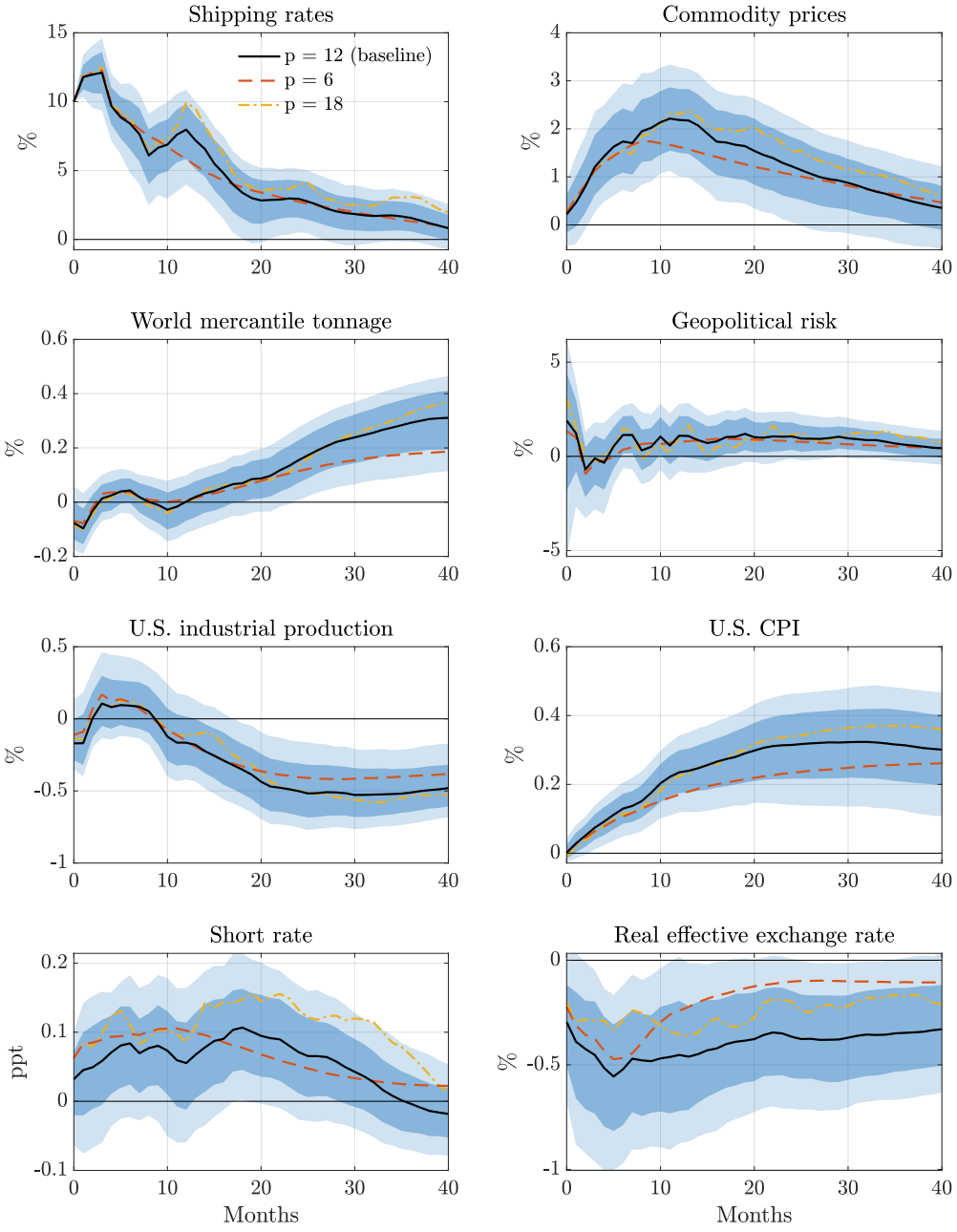
Uncertainty. To sharpen the interpretation of the shock, we study how supply chain shocks influence a range of uncertainty and risk measures. Figure 8a shows the responses of economic policy uncertainty, trade policy uncertainty, and crude oil volatility to a supply chain shock. None of these measures respond significantly, with the point estimates remaining close to zero and statistically insignificant throughout. This is reassuring, as it suggests that our identified shock represents a distinct source of supply chain disruption rather than a broader deterioration in economic or policy uncertainty, further supporting

Figure C.9: Excluding the Covid-19 period



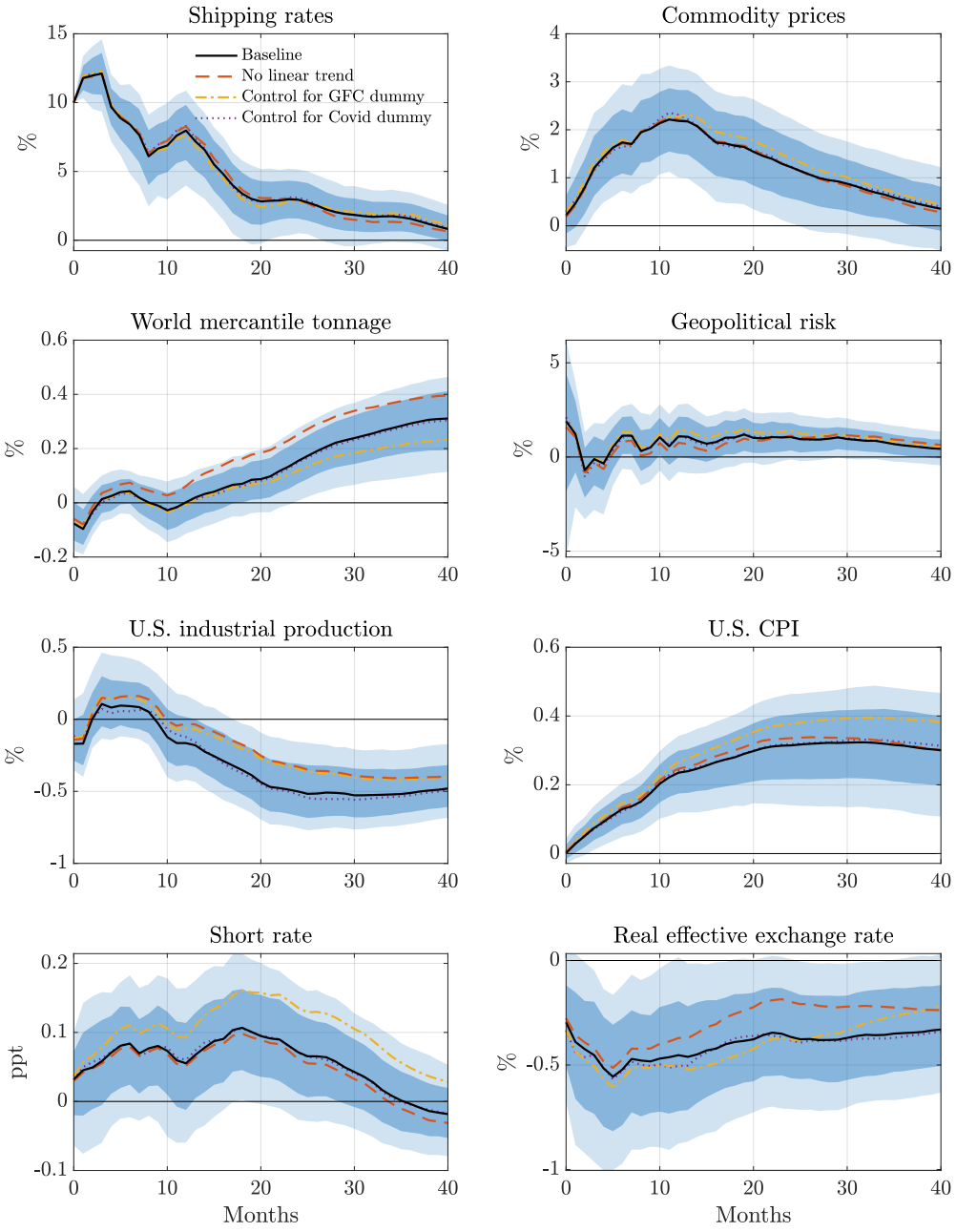
Notes: Impulse responses to a Impulse responses to a supply chain shock based on a sample excluding the Covid-19 period. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.10: Sensitivity With Respect to Lag Order



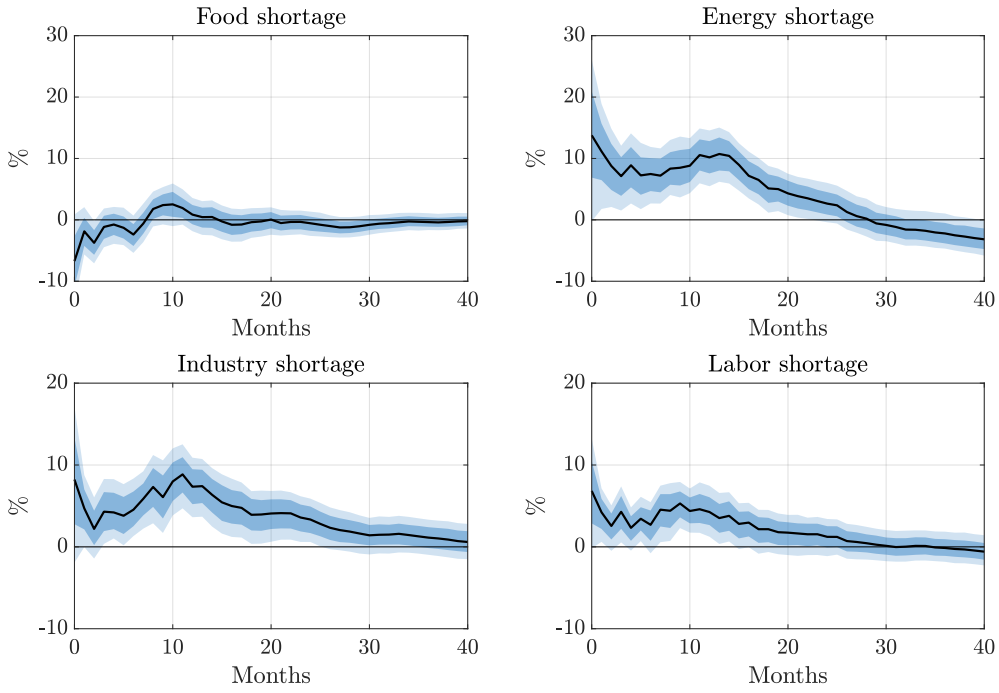
Notes: Impulse responses to a shipping cost shock with varying lag order. The lines are the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.11: Sensitivity With Respect to Deterministics



Notes: Impulse responses to a shipping cost shock using a model that excludes the linear trend and controls for the global financial crisis (GFC) and Covid-19 using a dummy variable. The lines are the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

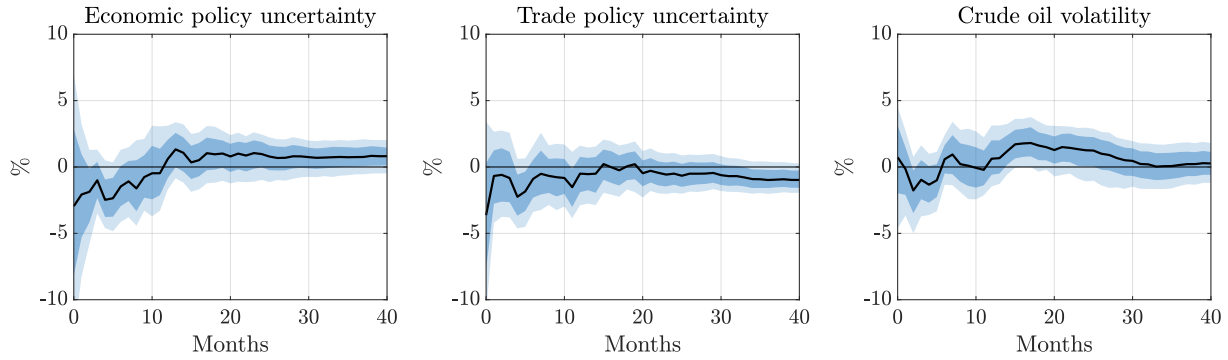
Figure D.1: Impacts on Shortage Measures



Notes: Impulse responses to a shipping cost shock, normalized to increase real shipping costs by 10 percent on impact. The IRFs are obtained by using our baseline VAR and augmenting it by the variable of interest. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

the validity of our identification strategy.

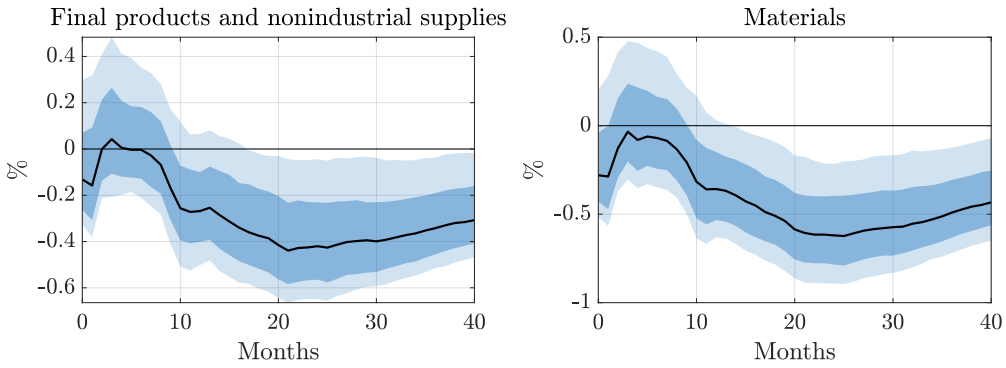
Figure D.2: Impacts on Other Uncertainty and Risk Measures



Notes: Impulse responses to a shipping cost shock, normalized to increase real shipping costs by 10 percent on impact. The IRFs are obtained by using our baseline VAR and augmenting it by the variable of interest. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Industrial production. Figure D.3 shows the responses of industrial production categories by market group to a supply chain shock. Both final products and non-industrial supplies and materials decline significantly following the shock, consistent with the broad-based disruption to production activity that supply chain shocks generate. The responses are qualitatively similar across the two components, though the decline in intermediate inputs is notably larger, reaching a trough of around 0.6 percent compared to 0.4 percent for final products. This pattern is intuitive — supply chain disruptions primarily impede the flow of intermediate inputs and raw materials, which bear the brunt of the shock before it propagates through to final goods production.

Figure D.3: Impact on Industrial Production Categories



Notes: Impulse responses to a shipping cost shock, normalized to increase real shipping costs by 10 percent on impact. The IRFs are obtained by using our baseline VAR and augmenting it by the variable of interest. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

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