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 based on disruptions at key locations like the Suez and Panama Canal, using narrative accounts and high-frequency financial data. These shocks lead to a significant and persistent increase in shipping costs, which in turn has substantial economic consequences. Economic activity falls significantly and producer and consumer prices rise persistently. Global shipping capacity initially contracts before expanding sluggishly in response to persistently elevated shipping costs. The shocks also lead to a significant increase delivery times and industry shortages but are not associated with changes in geopolitical risk—consistent with our interpretation of exogenous supply chain disruptions. Our reduced-form evidence provides new empirical targets for quantitative trade and network models.

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.

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 (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 short- and long-term substitution possibilities across firms and sectors. Our framework allows to obtain reduced-form elasticities of substitution across production factors, which can be used to discipline quantitative network models.

Our analysis also connects to the international trade literature, where iceberg trade costs are central to models of international production and shock transmission (Eaton and Kortum, 2002; Melitz, 2003). Recent work extends these frameworks to include production networks and global value chains, emphasizing how trade frictions influence the propagation of shocks across countries (Antràs and De Gortari, 2020; Caliendo and Parro, 2015; Costinot and Rodríguez-Clare, 2014). In this literature, trade elasticities are routinely calibrated based on aggregate flows. Direct evidence on the substitutability between domestic and foreign inputs in response to global supply chain shocks as well as the degree of heterogeneity in pass-through across countries is more limited—though notable exceptions include Boehm, Flaaen, and Pandalai-Nayar (2019) and Carvalho et al. (2021). Our reduced-form approach can offer empirical moments on both margins, providing useful discipline for structural trade models that seek to capture the macroeconomic implications of global trade frictions.

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 discuss how our estimates can be used to inform structural trade and network models. Section 6 concludes.

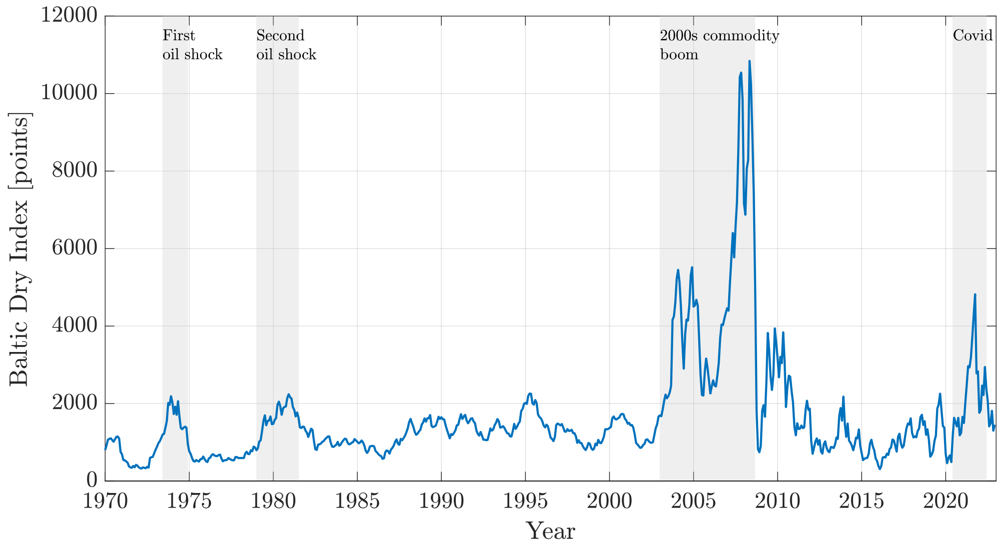
2. Identification Strategy

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

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



demand for commodities. The Covid-19 period saw a mix of both—disrupted logistics 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.

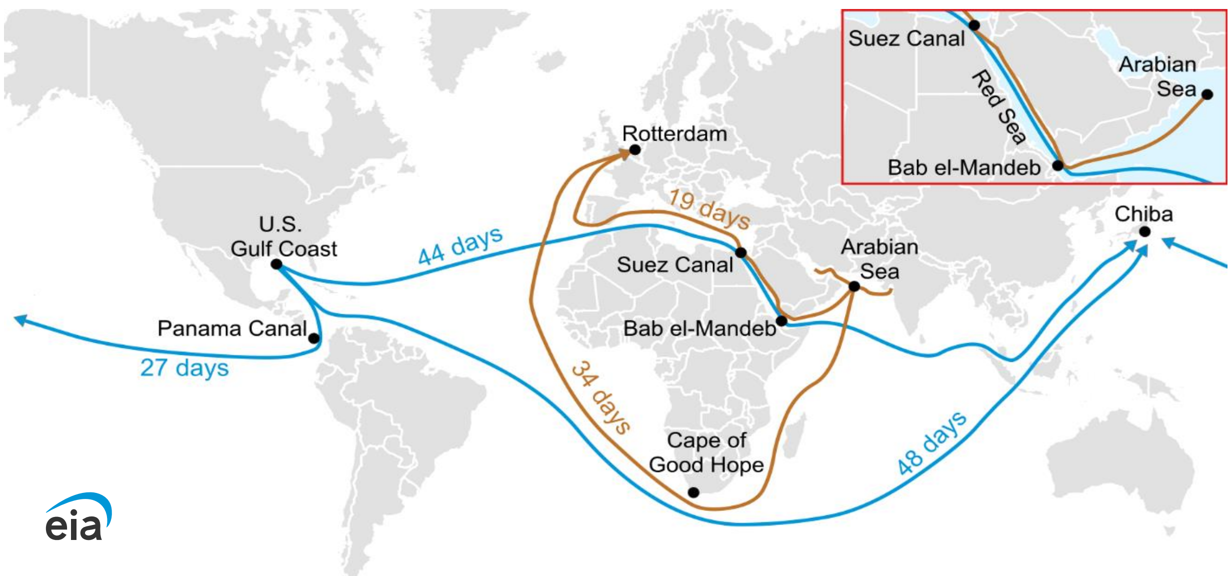
2.1. Choke Points in Global Supply Chains

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).

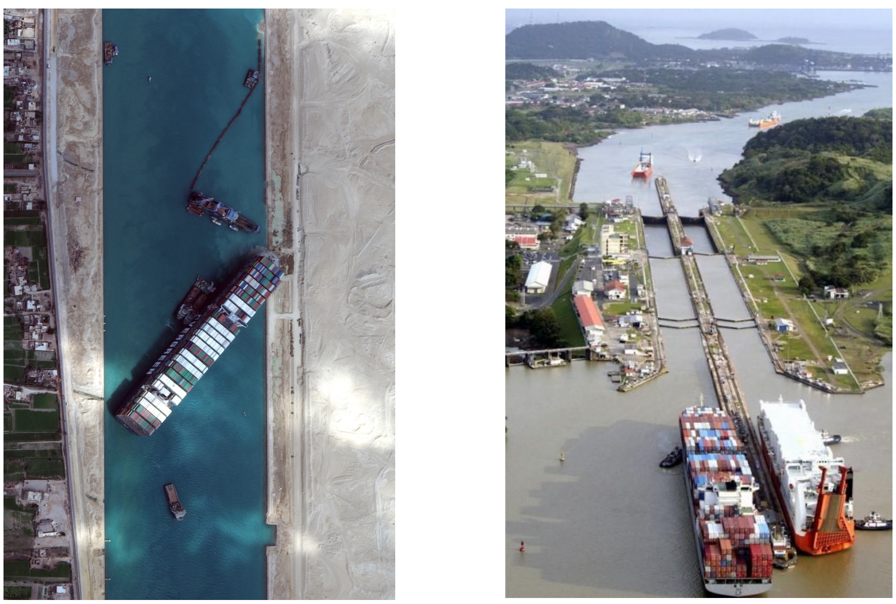
Throughout its history, the Suez Canal has experienced numerous disruptions to shipping traffic due to its narrow, constrained passage—from vessel groundings and collisions to fires, piracy incidents, and adverse weather conditions (see Figure 3a). One such notable and recent incident occurred on March 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 139 events that disrupted shipping traffic in the two canals between 1970 and 2022, including 94 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

Table 1: Disruptive Events at Maritime Choke Points

Panama Canal		Suez Canal	
Event Type	Number	Event Type	Number
Grounding	1	Grounding	57
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	94

Canal include 57 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.

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]

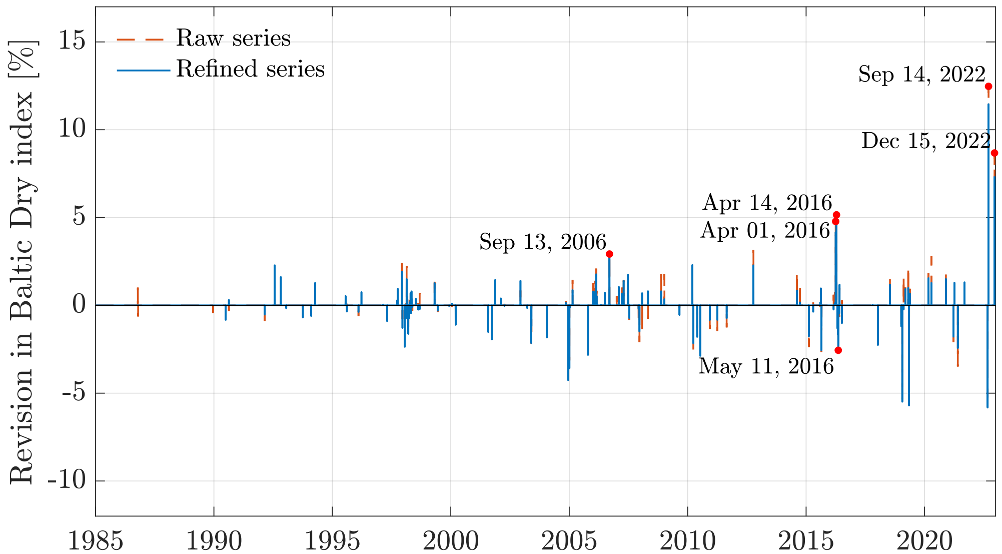
$$SCSurprise_d = \frac{P_d^{\text{BDI}} - P_{d-1}^{BDI}}{P_{d-1}^{\text{BDI}}}, \tag{1}$$

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

[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



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.

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 indicating 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 financial 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 statistically 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.

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.

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:

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

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 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-

[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.

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, $\mathbf{B}(L) \equiv \mathbf{I} + \mathbf{B}_1 L + \mathbf{B}_2 L^2 + \dots$ 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 $\mathbf{A}(L) \equiv \mathbf{I} - \mathbf{A}_1 L - \dots$ 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:

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

provided that $E[z_t \mathrm{u}_{1,t}] \neq 0$. 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 $\hat{\mathrm{u}}_{1,t}$ 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, $\bar{\mathbf{s}}_1 = [\mathrm{chol}(\bar{\boldsymbol{\Sigma}})]_{\cdot,1} / [\mathrm{chol}(\bar{\boldsymbol{\Sigma}})]_{1,1}$.

[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).

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 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.

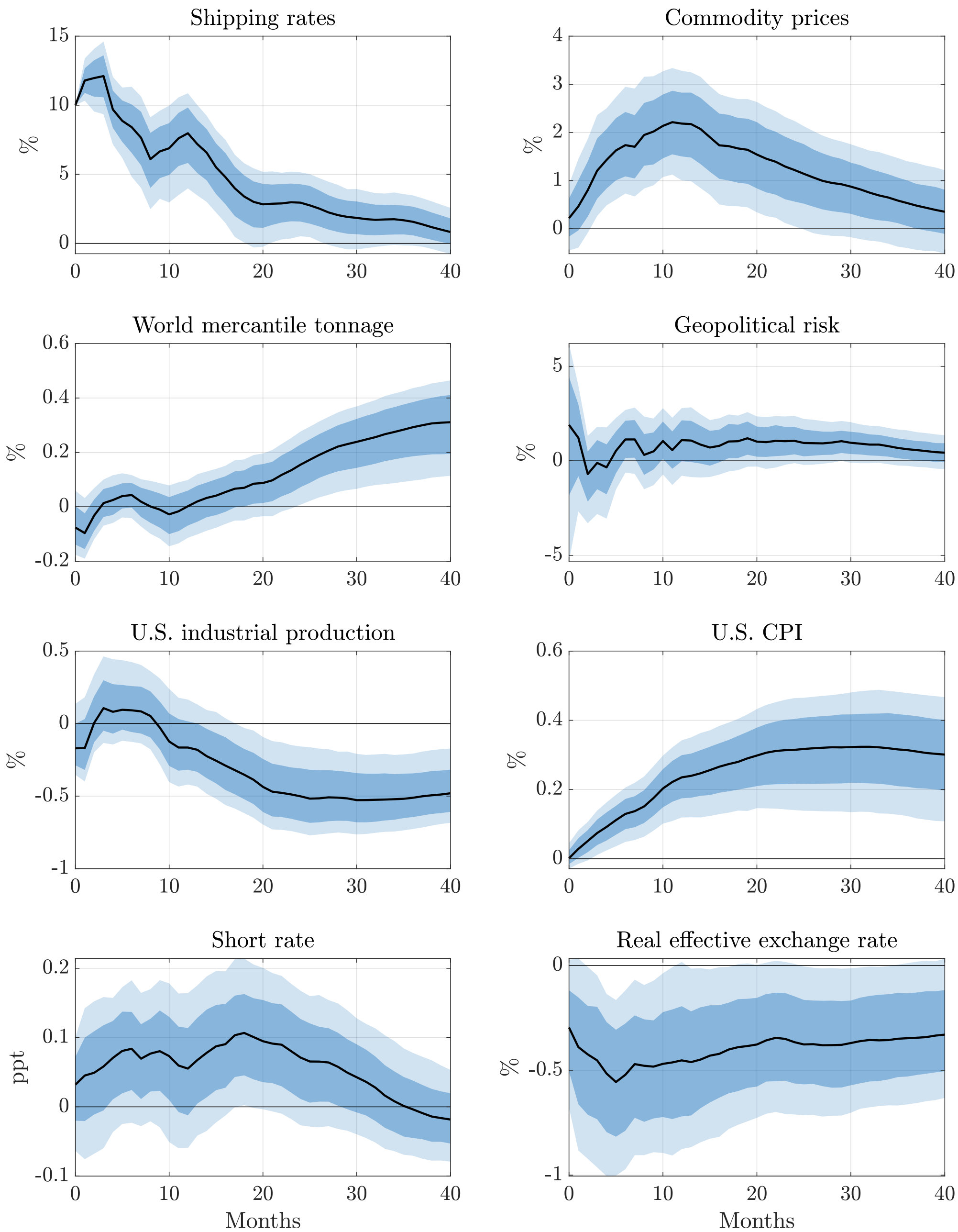
However, even if the surprise series is exogenous, standard inference will not produce reliable results when the instrument and the shock are only weakly correlated. In a first step, it is thus important to test the *strength* of the instrument. This can be done using an F-test in the first-stage regression 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

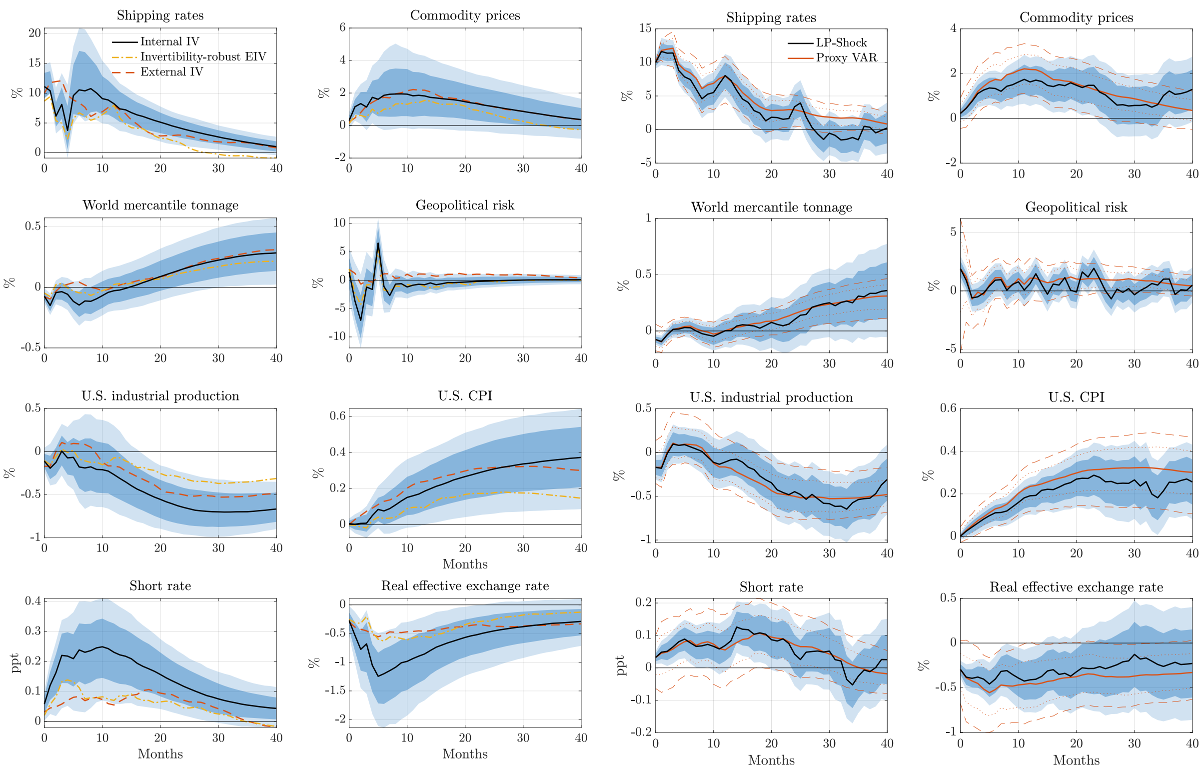
In this section, we assess the robustness of our results with respect to some of the key assumptions underlying our empirical approach. We also discuss potential identification concerns regarding our instrument.

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.4. 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.5-C.6 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.8).

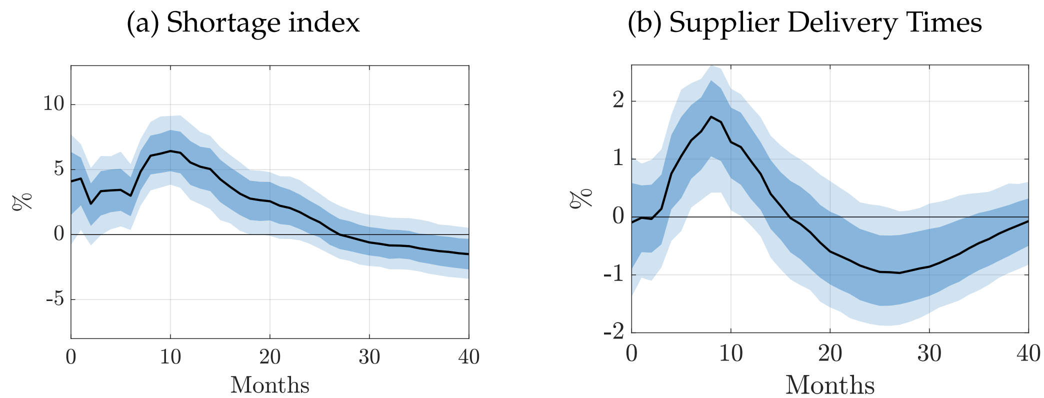
Finally, we explore how the predictability in our shipping cost surprises affects the results. We find consistent effects when restricting the sample to the first event in each sequence—those that are arguably least predictable—as well as when we forgo any attempt to remove predictability altogether, see Appendix Figures C.2 and C.9. 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 macroeconomic variables. We follow the approach outlined in Section 3.1 to compute the impulse responses for additional variables of interest.

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 7, 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 7: 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.

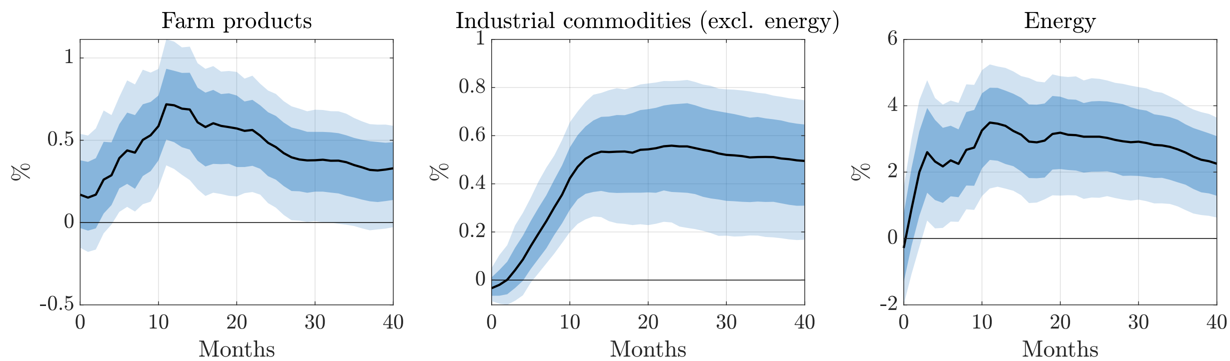
Geopolitical risk. Given the significant impact on energy shortages, one may be concerned that our approach largely captures geopolitical oil supply risk. This is why we did not include any disruptive events in the Strait of Hormuz. In selecting our events, we thus put great care into excluding disruptions 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 financial uncertainty, 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 8a, 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.

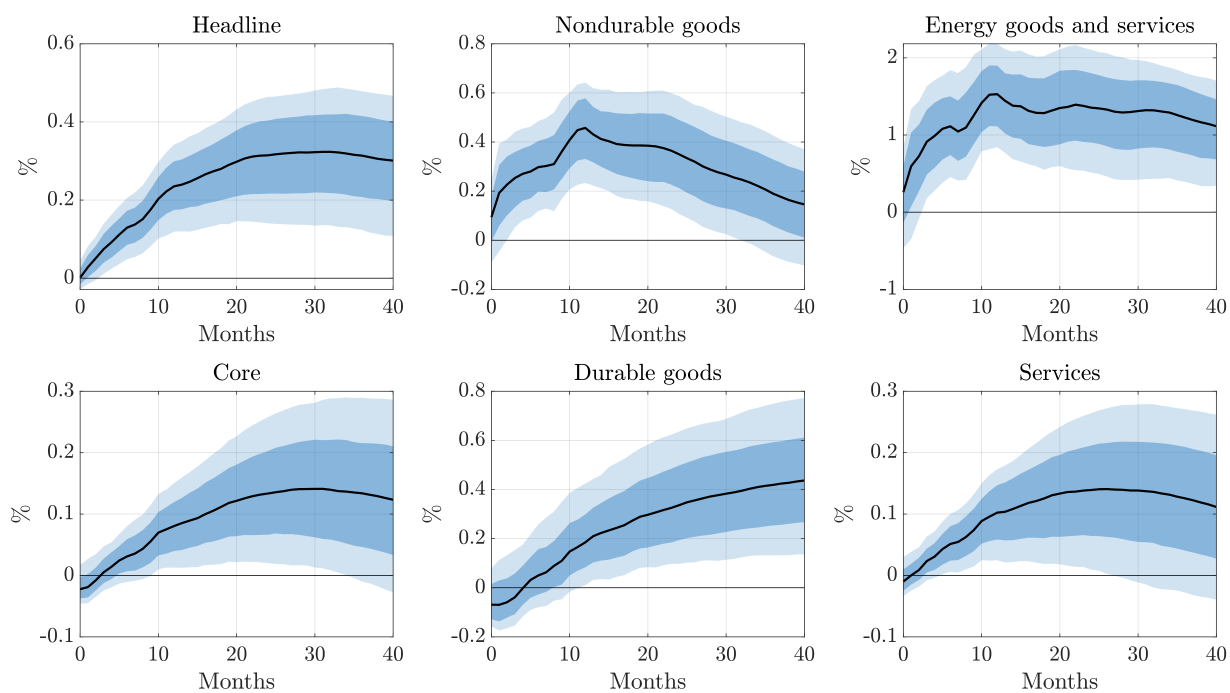
In terms of magnitude, energy prices increase the most, with a peak response of around 2 percent. This increase can be attributed to two factors. First, oil tankers account for approximately 30 percent of global fleet capacity, and an estimated 76 percent of world oil trade relies on seaborne routes. 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 in-

Figure 8: Impact on Producer and Consumer Prices

(a) Producer Prices



(b) Consumer Prices



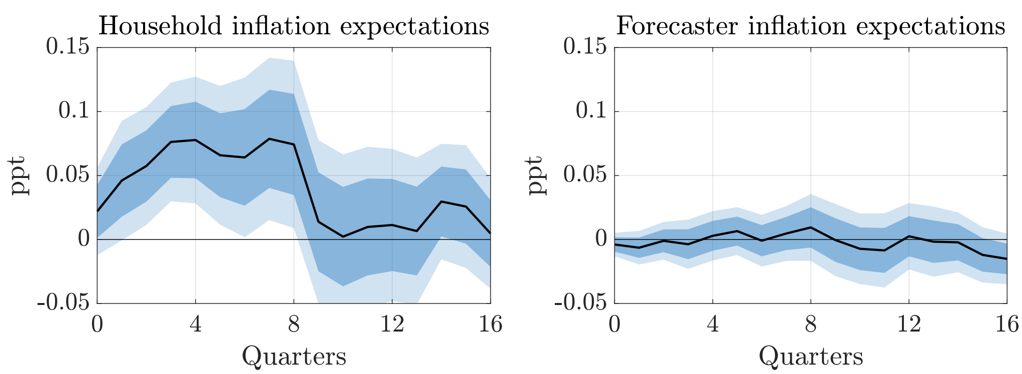
Notes: Impulse responses to a supply chain shock, normalized to increase real shipping costs by 10 percent on impact. The IRFs are obtained by using our baseline VAR and augmenting it by the variable of interest. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent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

crease 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 8b, 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 9 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.

Figure 9: Inflation Expectations



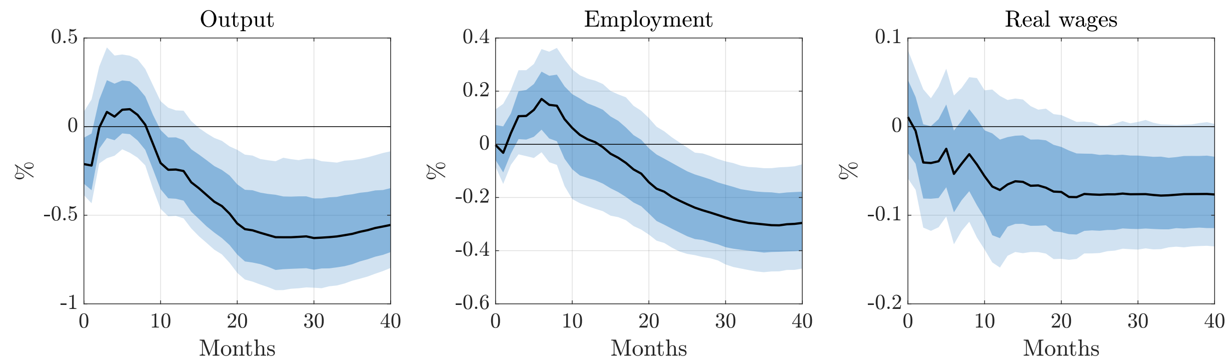
Notes: Impulse responses to a supply chain shock, normalized to increase real shipping costs by 10 percent on impact. The IRFs are obtained by using our baseline VAR and augmenting it by the variable of interest. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent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

Economic activity. Shipping disruptions delay the transport of essential industrial materials, raising costs for manufacturers. In Figure 10a, we can see that manufacturing output falls significantly. Interestingly, employment tends to increase in the short run—possibly pointing to some substitution from other inputs to labor—before falling significantly. Real wages tend to decrease but the response is not very precisely estimated.

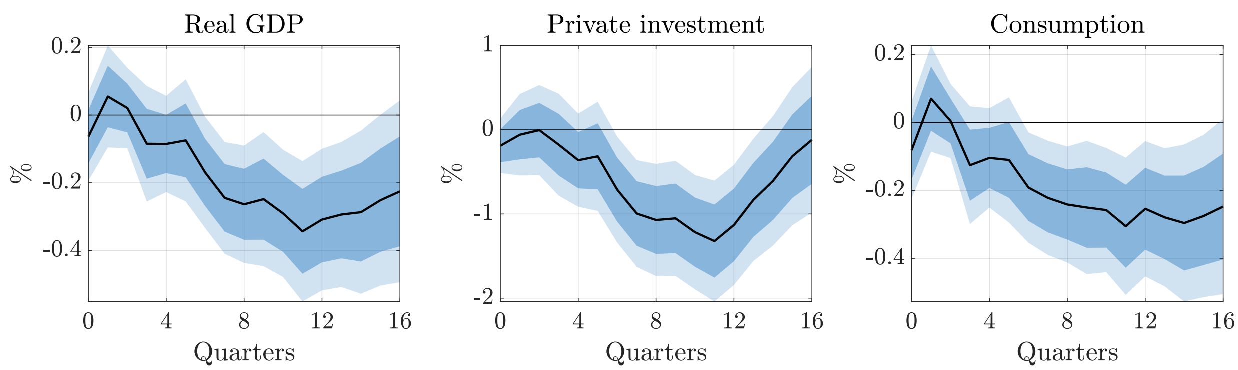
The substantial impacts on industrial production and manufacturing in particular translates into more broad based economic effects. Figure 10b shows the responses of real GDP, private investment and consumption. A supply chain shock leads to a fall in output and its components. At peak, real GDP falls by about 0.25 percent, investment by 1 percent, and consumption by 0.2 percent.

Figure 10: Impact on Economic Activity

(a) Manufacturing Sector



(b) Broader Impacts

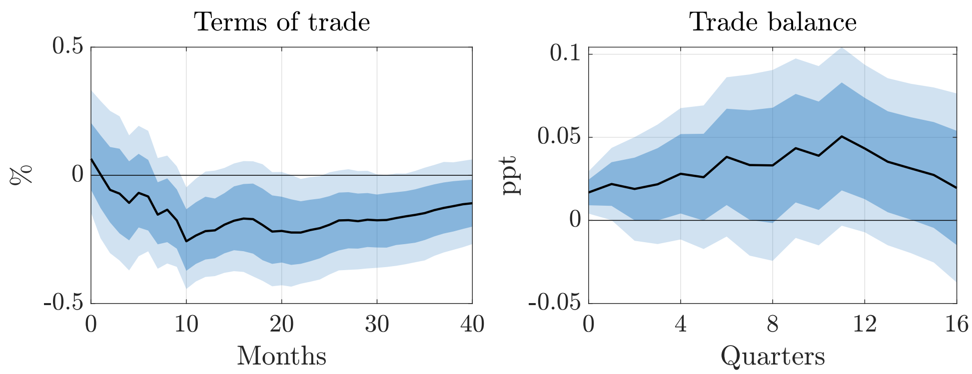


Notes: Impulse responses to a supply chain shock, normalized to increase real shipping costs by 10 percent on impact. The IRFs in Panel (a) are obtained by using our baseline VAR and augmenting it by the variable of interest. The lines are point estimates and the dark and light shaded areas are 68 and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

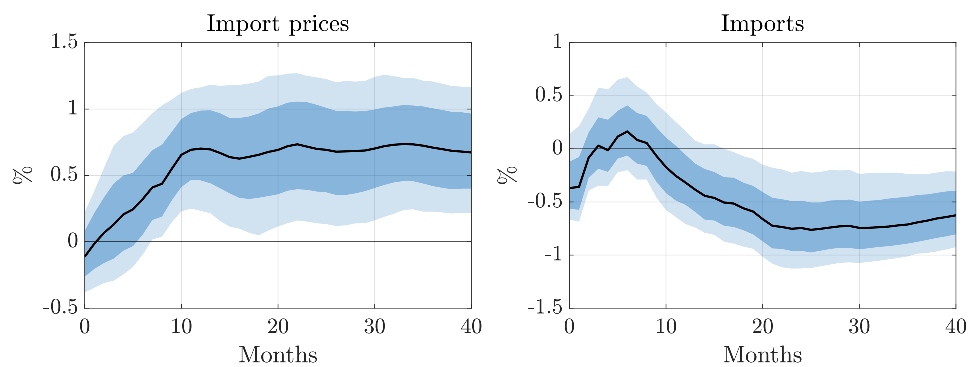
Trade. Supply chain shocks also have significant effects on trade. Figure 11 shows that the shock leads to a significant fall in the terms of trade. The trade balance, however, improves, consistent with the depreciation of the dollar. In the bottom panels we can see that these responses are driven by a significant increase in import prices and a fall in imports.

Figure 11: Impact on Trade

(a) Terms of Trade and Trade Balance



(b) Import Prices and Flows



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.

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 in inflation observed in 2022.

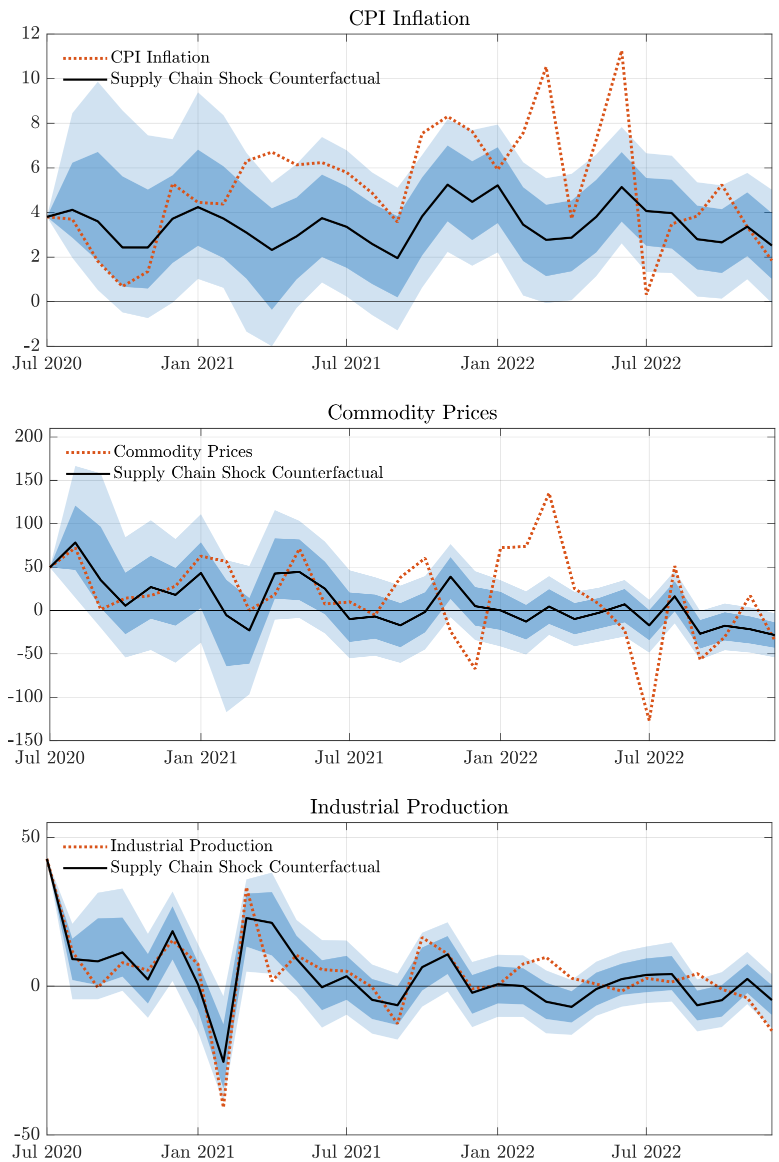
The same pattern is evident in commodity price dynamics. Supply chain disruptions explain a sizable portion of the fluctuations in commodity prices throughout 2021, reflecting their role in affecting global transportation costs and intermediate input availability. Yet, they fall short of accounting for 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

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

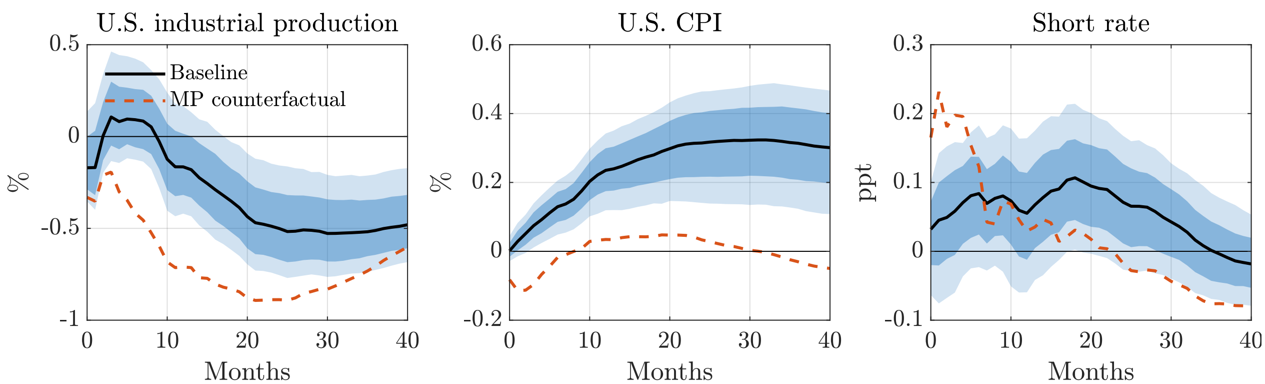


Notes: Counterfactual evolution of CPI inflation, commodity prices inflation and industrial production growth when turning off all other shocks but supply chain shocks from mid-2020 to 2022 (black line), together with the actual evolution of these variables (dashed red line). The dark and light shaded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

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.

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.

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 inflationary 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. Implications for Trade and Network Models

Our reduced-form evidence on supply chain shocks provides new empirical targets to discipline structural trade and network models. We discuss two applications: elasticities of substitution across production factors and trade costs.

First, our reduced-form estimates offer an empirical foundation for investigating the role of trade costs in shaping the international transmission of supply chain shocks. Our plausibly exogenous shipping disruptions can serve as a natural proxy for changes in iceberg trade costs. Extending our analysis to cross-country outcomes allows to trace how input prices and quantities respond across national borders, offering reduced-form evidence on the elasticity of substitution between domestic and foreign inputs. Such evidence helps shed light on how trade costs shape sourcing decisions and the reallocation of trade flows in response to global disruptions. Moreover, heterogeneity in pass-through magnitudes across countries can inform variation in underlying trade frictions, such as differences in institutional quality, port efficiency, or contract structure.

Second, we can extend our approach to study changes in input prices and input use across different sectors in response to a supply chain shock. Based on these responses, we can estimate elasticities of substitution across production inputs in a structural production network setting. To fix ideas, consider a CES production framework in which sectoral output is generated using capital, labor, and a composite of intermediate inputs. In particular, let output in sector i at time t be given by:

$$Y_{it} = \left(\left[A_{it} K_{it}^{\alpha} L_{it}^{1-\alpha} \right]^{\frac{\zeta_i - 1}{\zeta_i}} + \left(B_{it} M_{it} \right)^{\frac{\zeta_i - 1}{\zeta_i}} \right)^{\frac{\zeta_i}{\zeta_i - 1}}, \quad \text{with} \quad M_{it} = \left(\sum_j \omega_{ij}^{\frac{1}{\eta_i}} Y_{ijt}^{\frac{\eta_i - 1}{\eta_i}} \right)^{\frac{\eta_i}{\eta_i - 1}},$$

where M_{it} is a CES aggregator of intermediate goods sourced from other sectors. The parameter ζ_i governs the elasticity of substitution between the value-added composite and intermediates, while η_i governs substitution across intermediate suppliers.

By estimating how relative input prices and quantities change in response to a supply chain shock, we can obtain reduced-form estimates of substitution elasticities. For instance, the elasticity between labor and intermediates can be identified from:

$$\zeta_{it} = \frac{\partial \ln \left(L_{it} / M_{it} \right)}{\partial \ln \left(P_{it}^{M} / W_t \right)},$$

where P_{it}^{M} is the price of intermediates and W_t is the wage. Since our identification relies on plausibly exogenous variation in global shipping costs, these elasticities are not biased by endogenous input price movements.

These elasticities can serve as useful targets to discipline quantitative trade and network models. We are currently working on estimating them using our framework and plan to provide these estimates in the next iteration of the draft.

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 persitently 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.

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 139 events that disrupted shipping traffic between 1970 and 2022, including 94 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.

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.

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.

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

Table A.1: Data Description, Sources, and Coverage

Variable	Description	Source	Trans.
Instrument			
BDIY	Baltic dry index (monthly average), extended using Hamilton (2021)	Bloomberg	$100 \times \Delta \log$
Baseline			
BDIY	Baltic dry index (monthly average), extended using Hamilton (2021)	Bloomberg	$100 \times \log$
BCOM	Bloomberg commodity index (monthly average)	Bloomberg	$100 \times \log$
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	$100 \times \log$
GPR	Geopolitical risk index from Caldara and Iacoviello (2022)	GPR index webpage	$100 \times \log$
INDPRO	U.S. industrial production: total index (2017 = 100; seasonally adjusted)	FRED	$100 \times \log$
PCEPI	Personal consumption expenditures: chain-type price index (2017 = 100; seasonally adjusted)	FRED	$100 \times \log$
SPX	S&P 500 index (monthly average)	Bloomberg	$100 \times \log$
TB3MS	3-Month treasury bill secondary market rate, discount basis	FRED	Level
RNUSBIS	Real narrow effective exchange rate for United States	FRED	Level
Additional Variables			
SHORTAGE	Shortage index from Caldara, Iacoviello, and Yu (2024)	Shortage index webpage	$100 \times \log$
DELIVERIES	Supplier delivery times, ISM	Bloomberg	$100 \times \log$

Figure A.1: Transformed Data Series

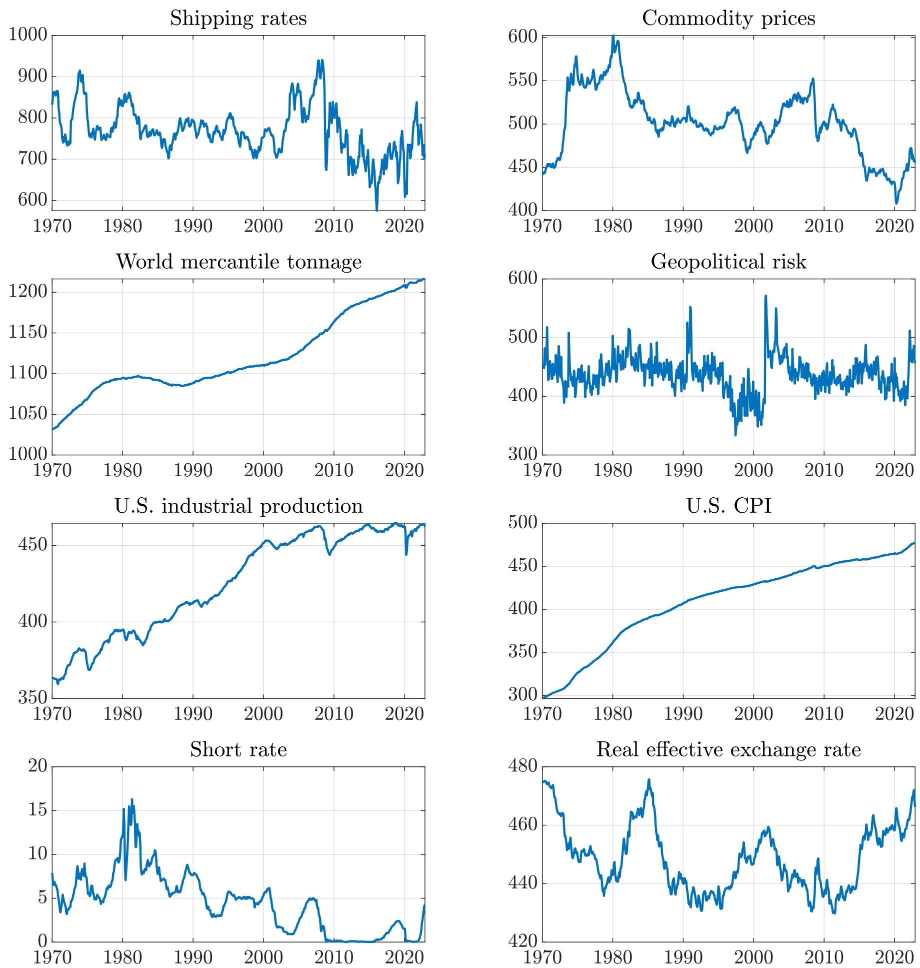
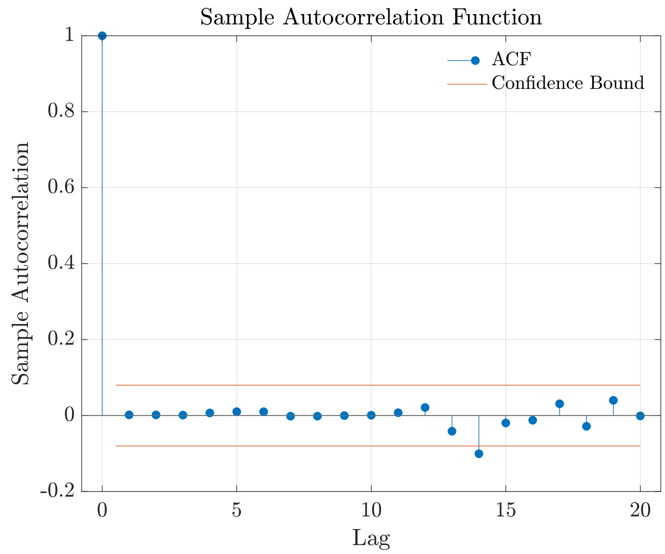


Figure B.1: Autocorrelation Function



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.

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

Event selection. Figure C.1 shows the responses using an instrument that excludes collisions.

Figure C.2 shows the responses using an instrument that relies on a more restrictive set of events or draft restrictions.

Figure C.3 shows the responses from a jackknife exercise in which one value of the surprise series is set to zero at a time.

Canals. Figure C.4 shows the responses using an instrument that includes events in the Panama canal or in the Suez canal alone.

Sample. Figure C.5 presents responses based on a sample excluding the 1970s, while Figure C.6 presents responses based on a sample excluding the Covid-19 period.

Negative surprises. Figure C.7 shows the responses using an instrument that censors negative surprises to zero.

Event window. Figure C.8 shows the responses using an instrument with surprises computed over a longer event window.

Predictability. Figure C.9 shows the responses using the raw instrument.

Model specification. Figures C.10 and C.11 show the results of sensitivity checks with respect to additional specification choices, including the lag order and deterministics.

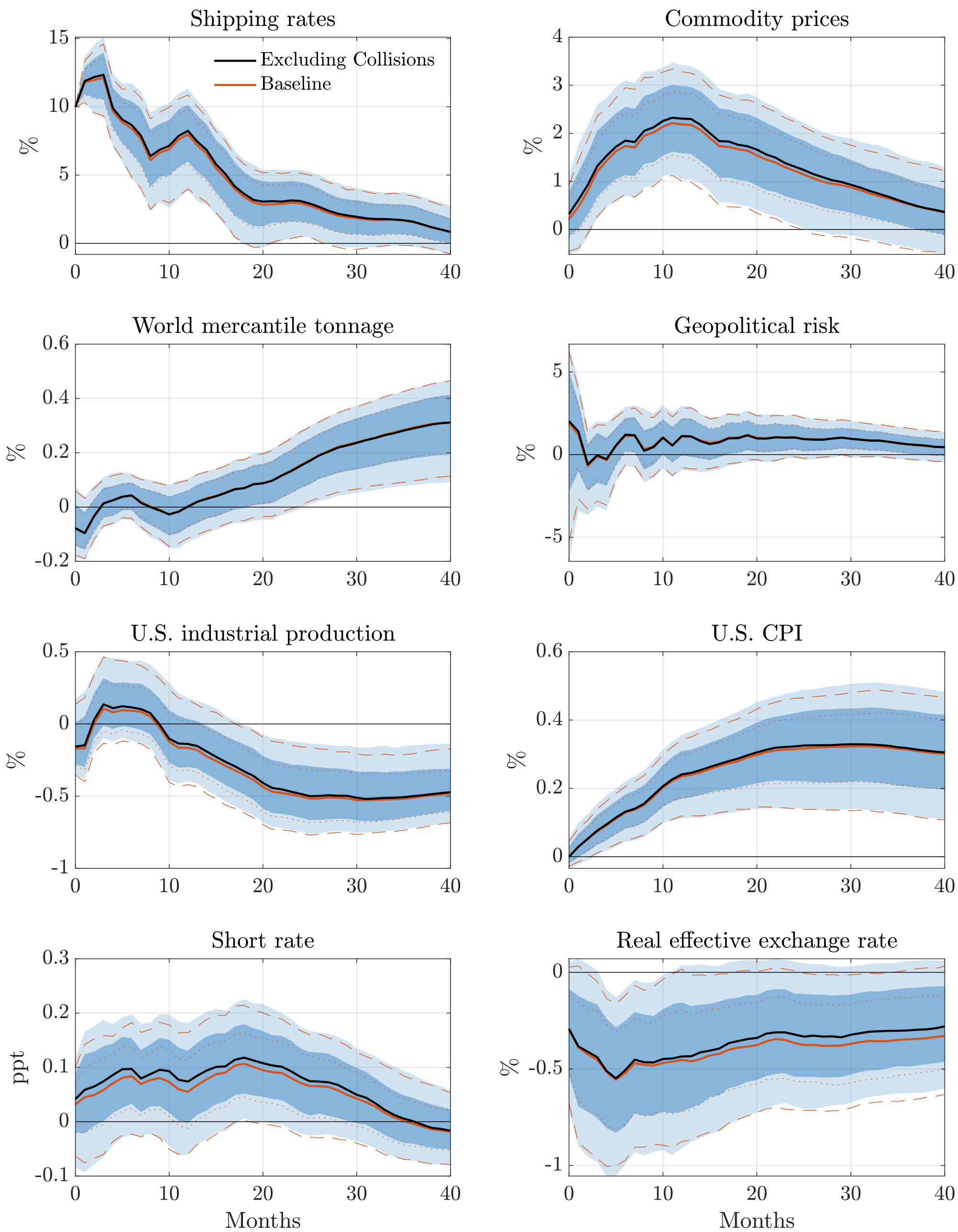
D. Additional Results

Shortages. Figure 7a shows the responses of the components of the shortage index constructed by Caldara, Iacoviello, and Yu (2024) to a shipping cost shock.

Uncertainty. Figure 7a shows the responses of various measures of uncertainty to a shipping cost shock.

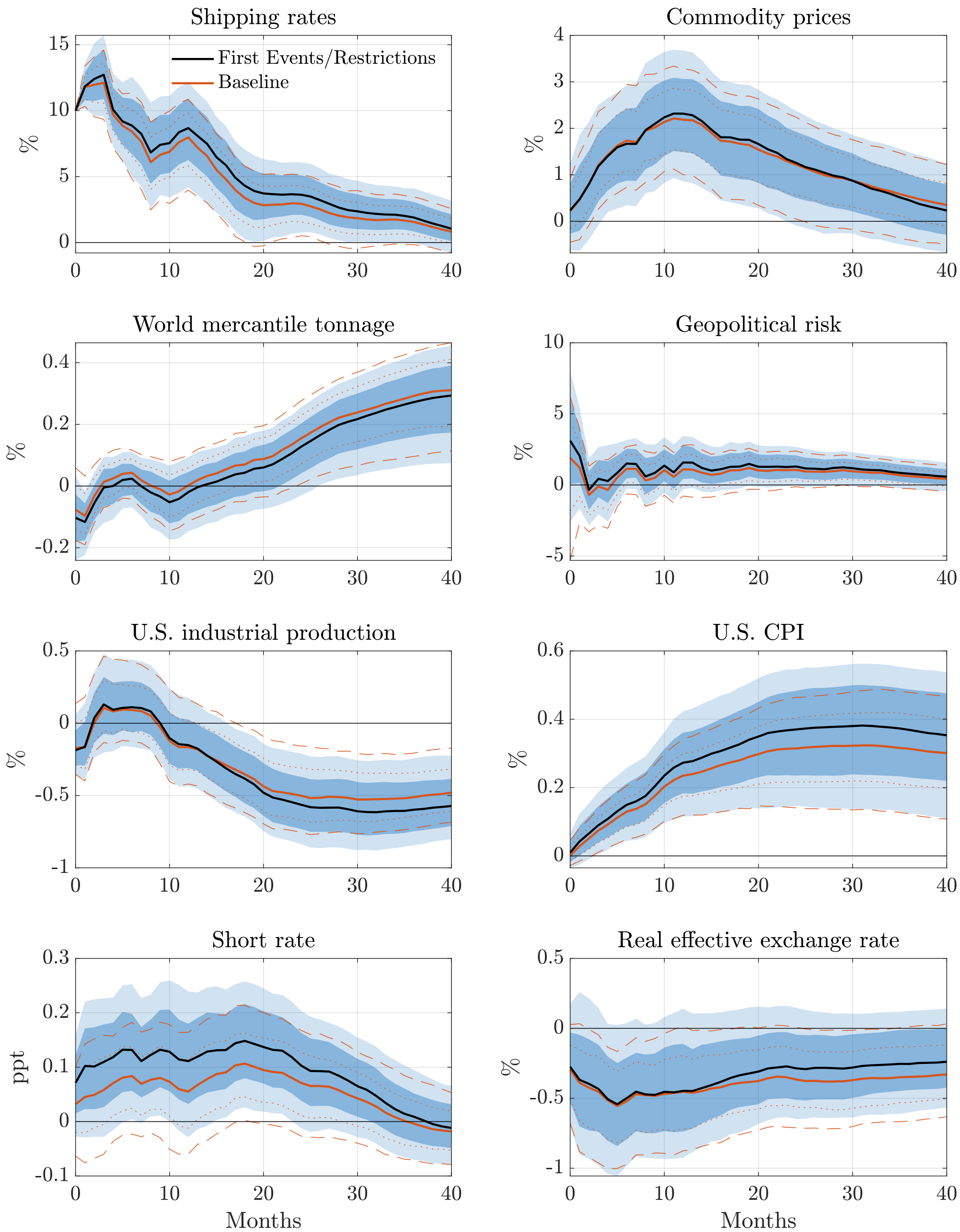
Industrial production. Figure D.3 shows the response of industrial production categories by market group to a shipping cost shock.

Figure C.1: Sensitivity With Respect to Excluding Collisions



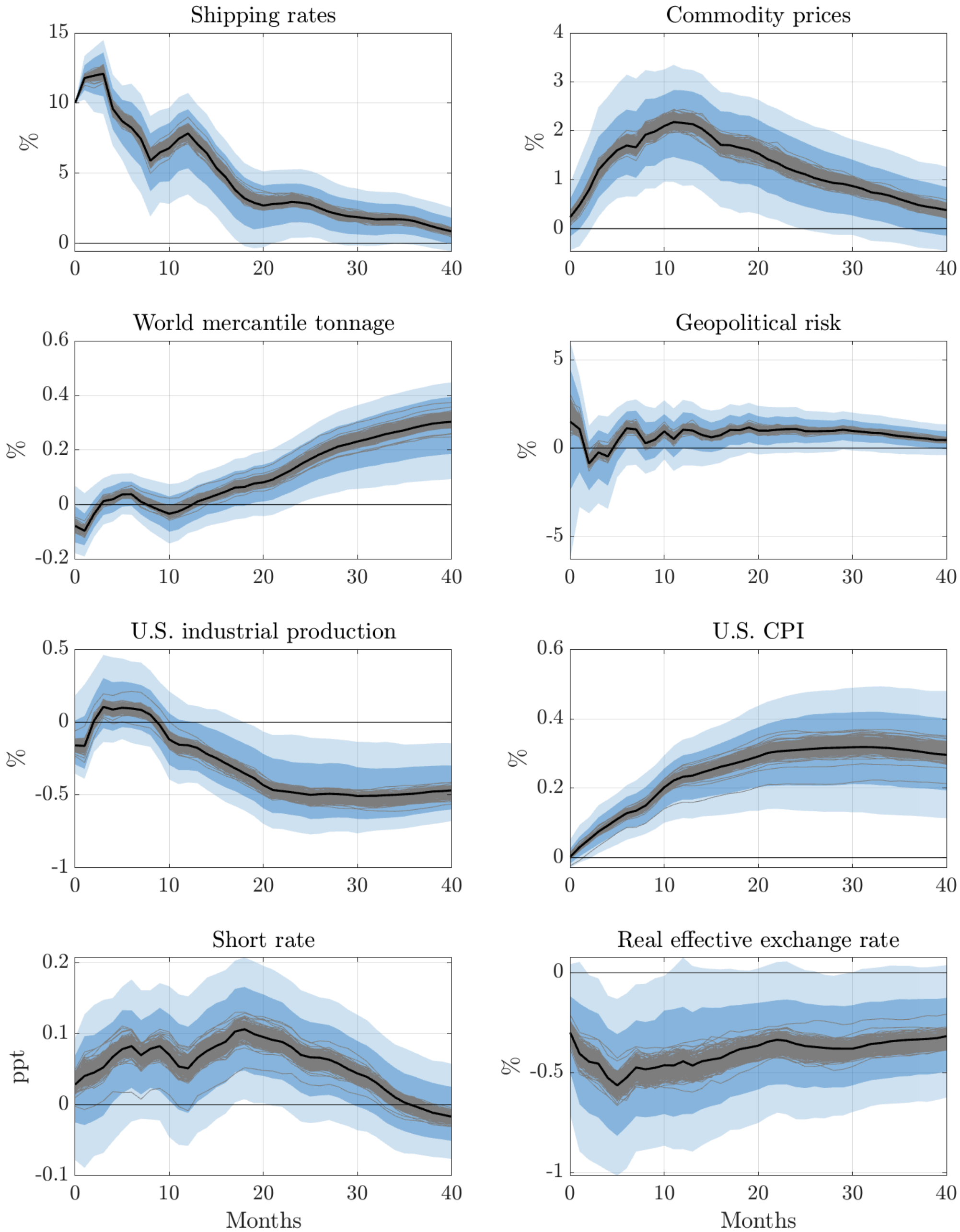
Notes: Impulse responses to a supply chain shock using an instrument that excludes collisions. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.2: Sensitivity With Respect to Event Selection



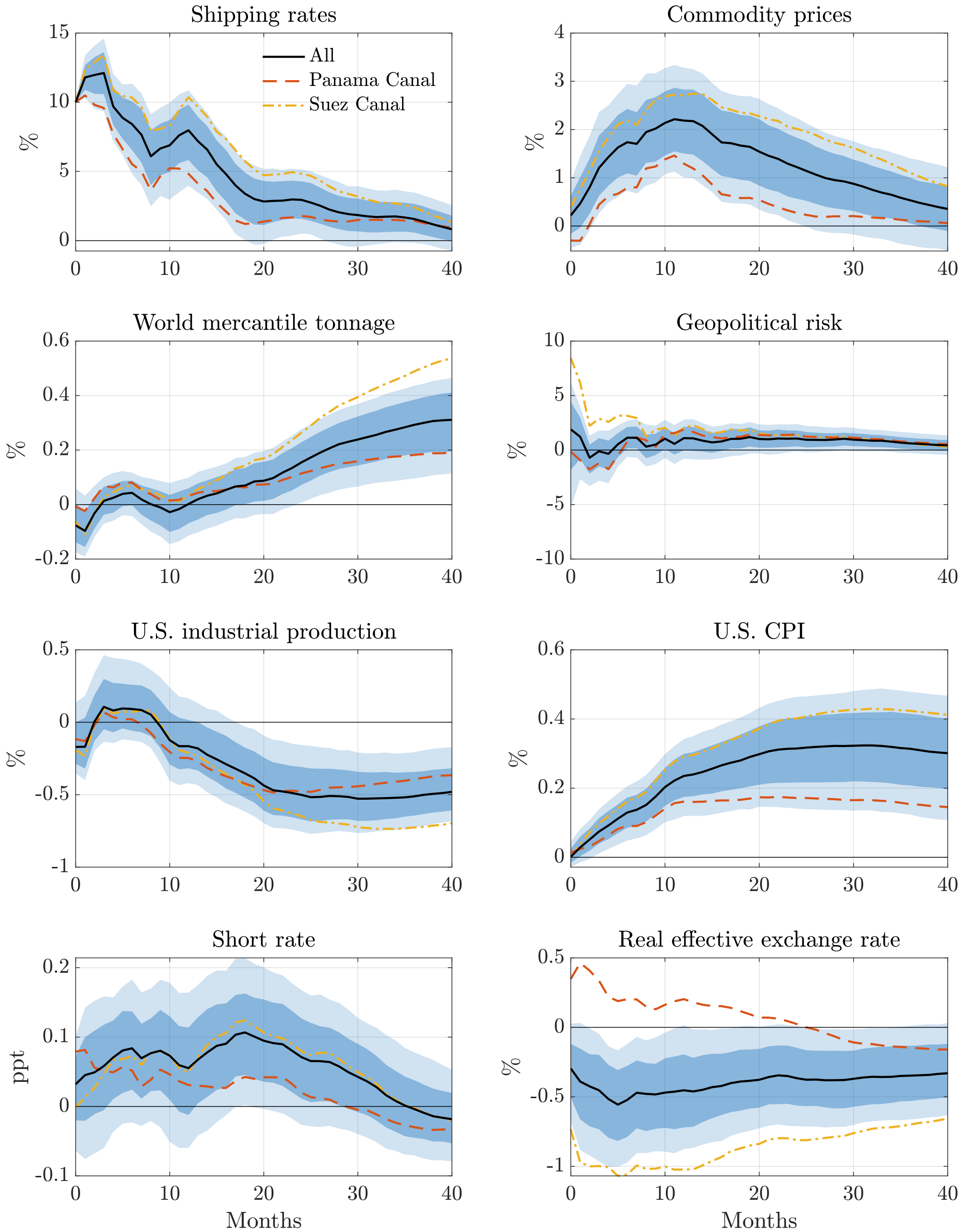
Notes: Impulse responses to a supply chain shock using an instrument that relies on a more restrictive set of events or draft restrictions. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.3: Jackknife Exercise



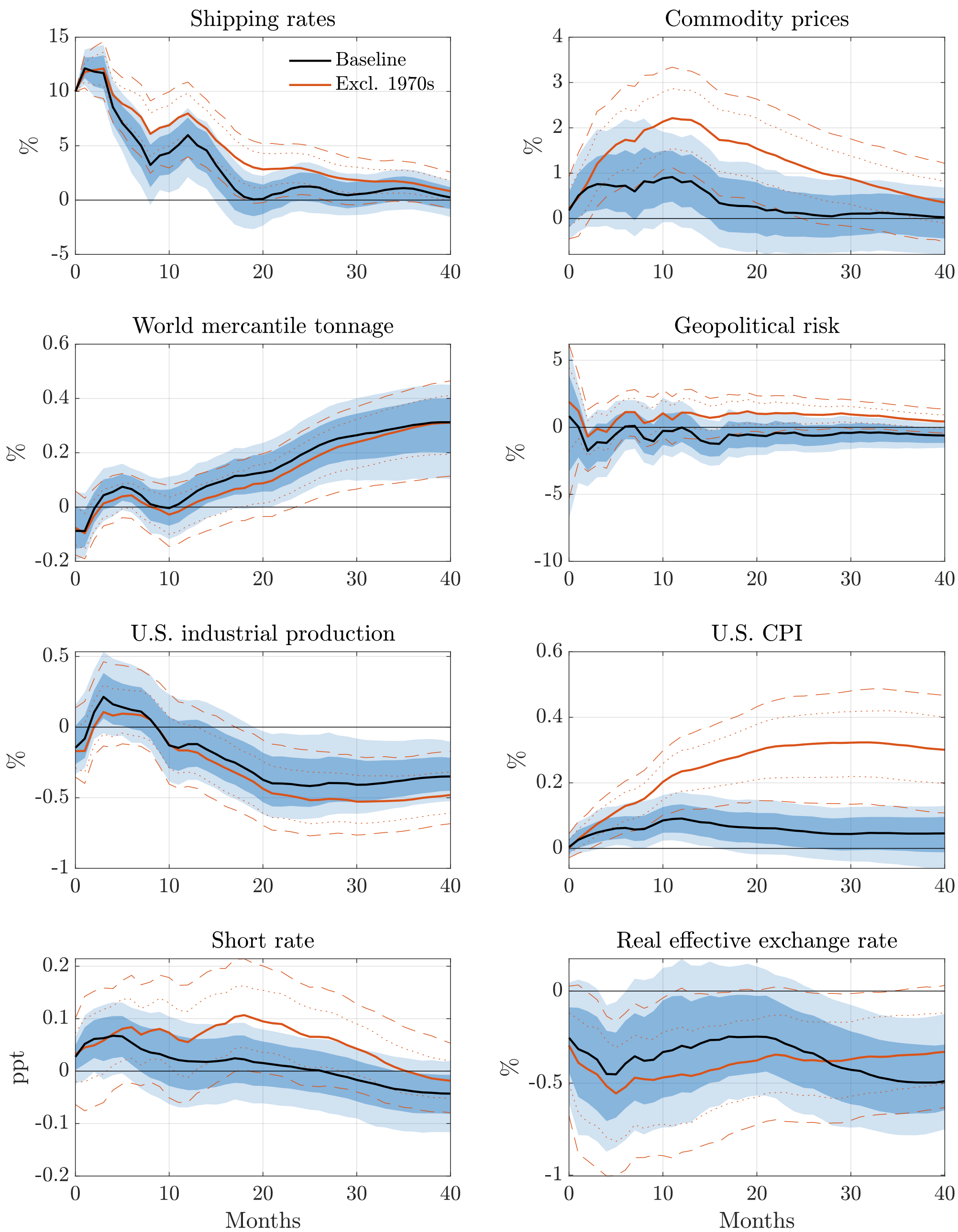
Notes: Impulse responses to a supply chain shock from the jackknife exercise. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.4: Sensitivity With Respect to Canals



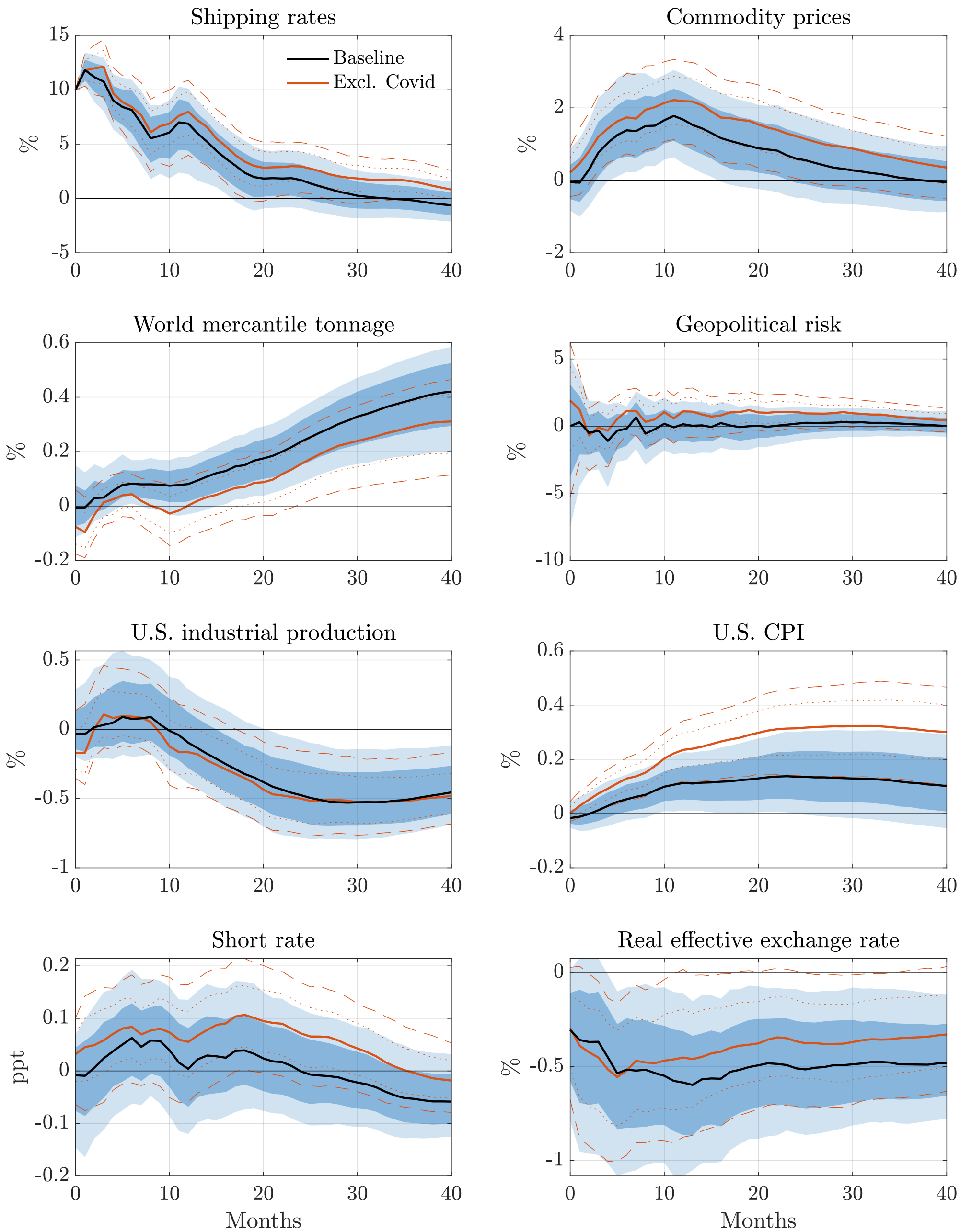
Notes: Impulse responses to a supply chain shock using an instrument that includes events in the Panama canal or in the Suez canal alone. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.5: Excluding the 1970s



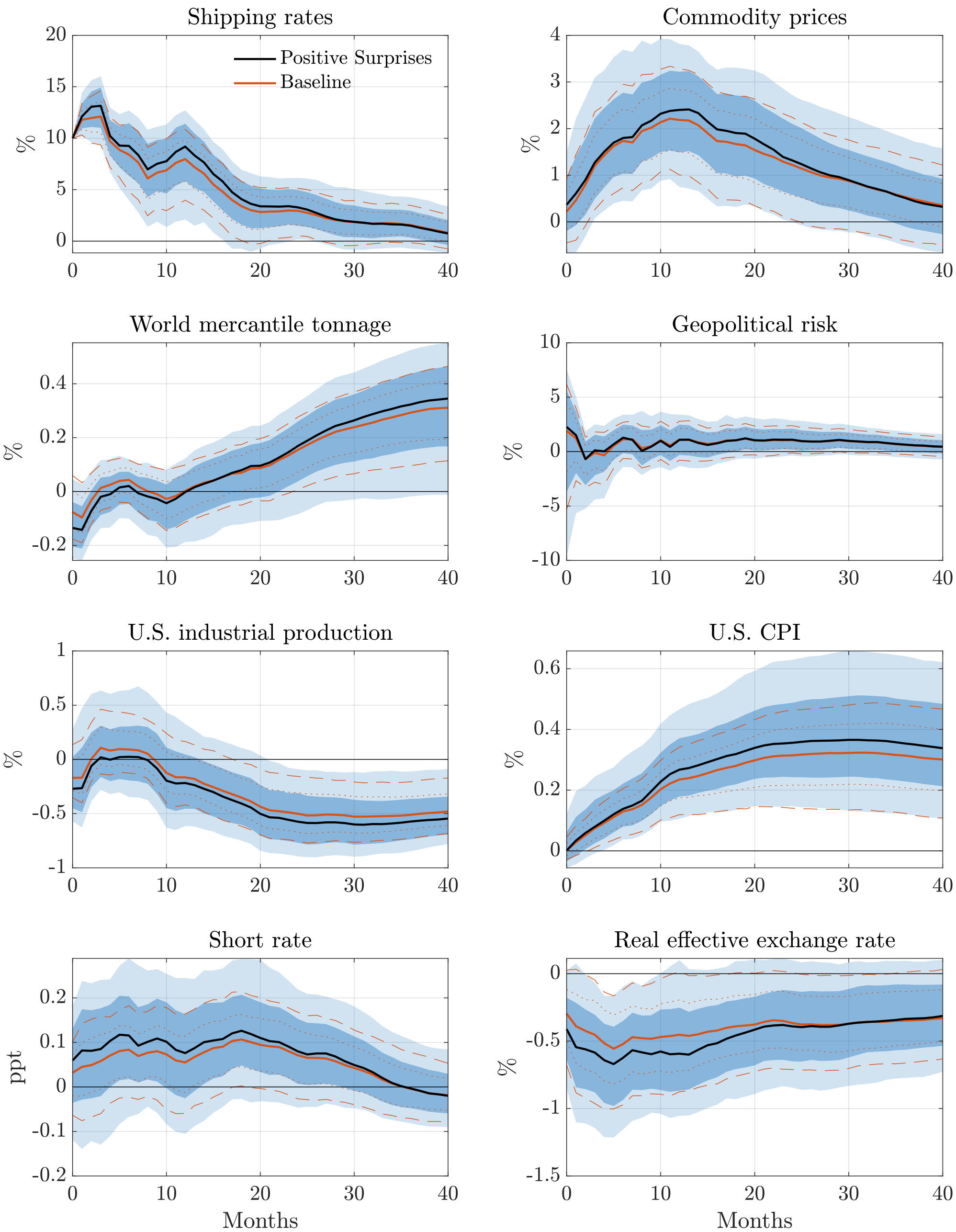
Notes: Impulse responses to a supply chain shock based on a sample excluding the 1970s. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.6: Excluding the Covid-19 period



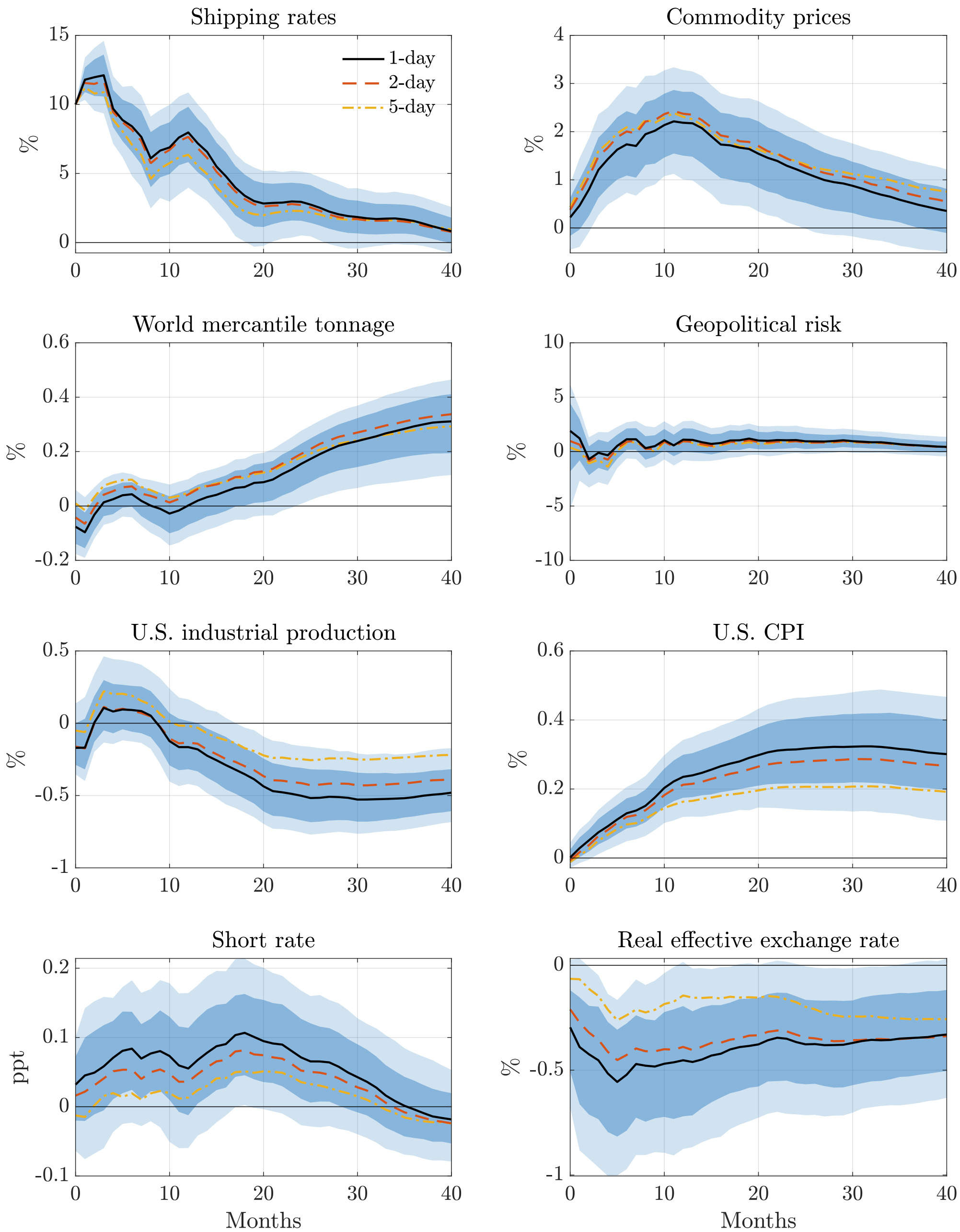
Notes: Impulse responses to a Impulse responses to a supply chain shock based on a sample excluding the Covid-19 period. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.7: Sensitivity With Respect to Negative Surprises



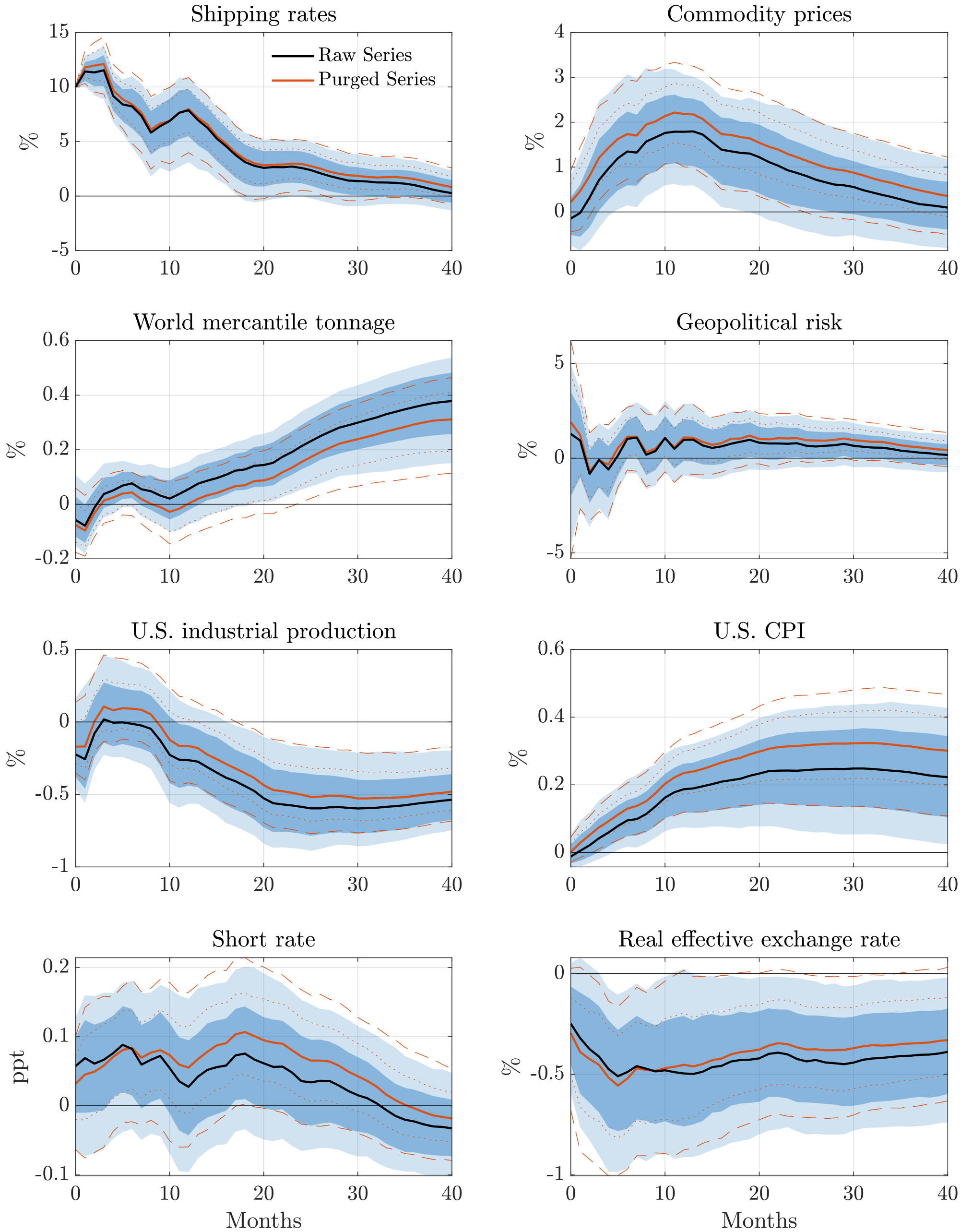
Notes: Impulse responses to a supply chain shock using an instrument that censors negative surprises to zero. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.8: Sensitivity With Respect to Event Window



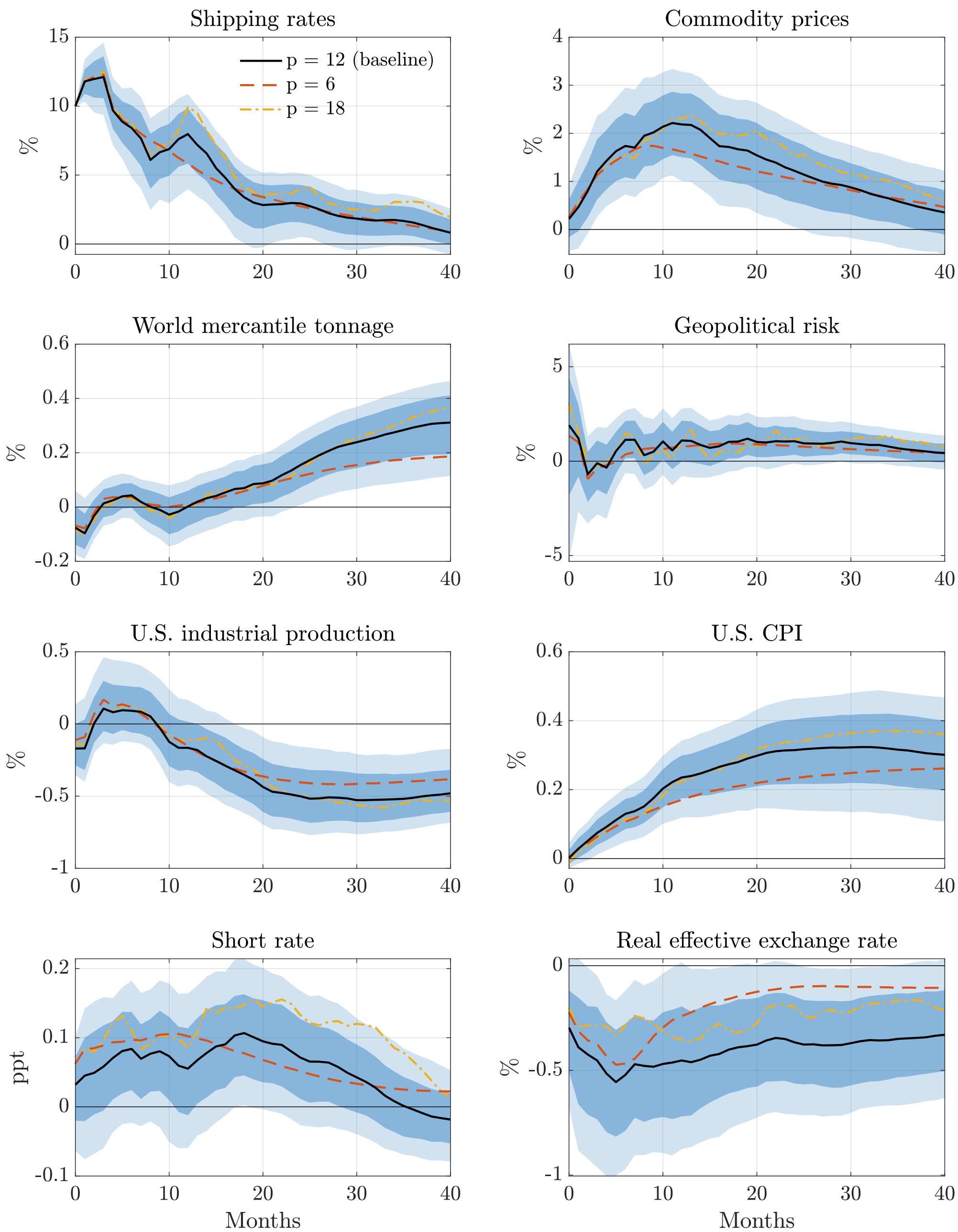
Notes: Impulse responses to a supply chain shock using an instrument with surprises computed over a longer event window. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.9: Raw Surprises



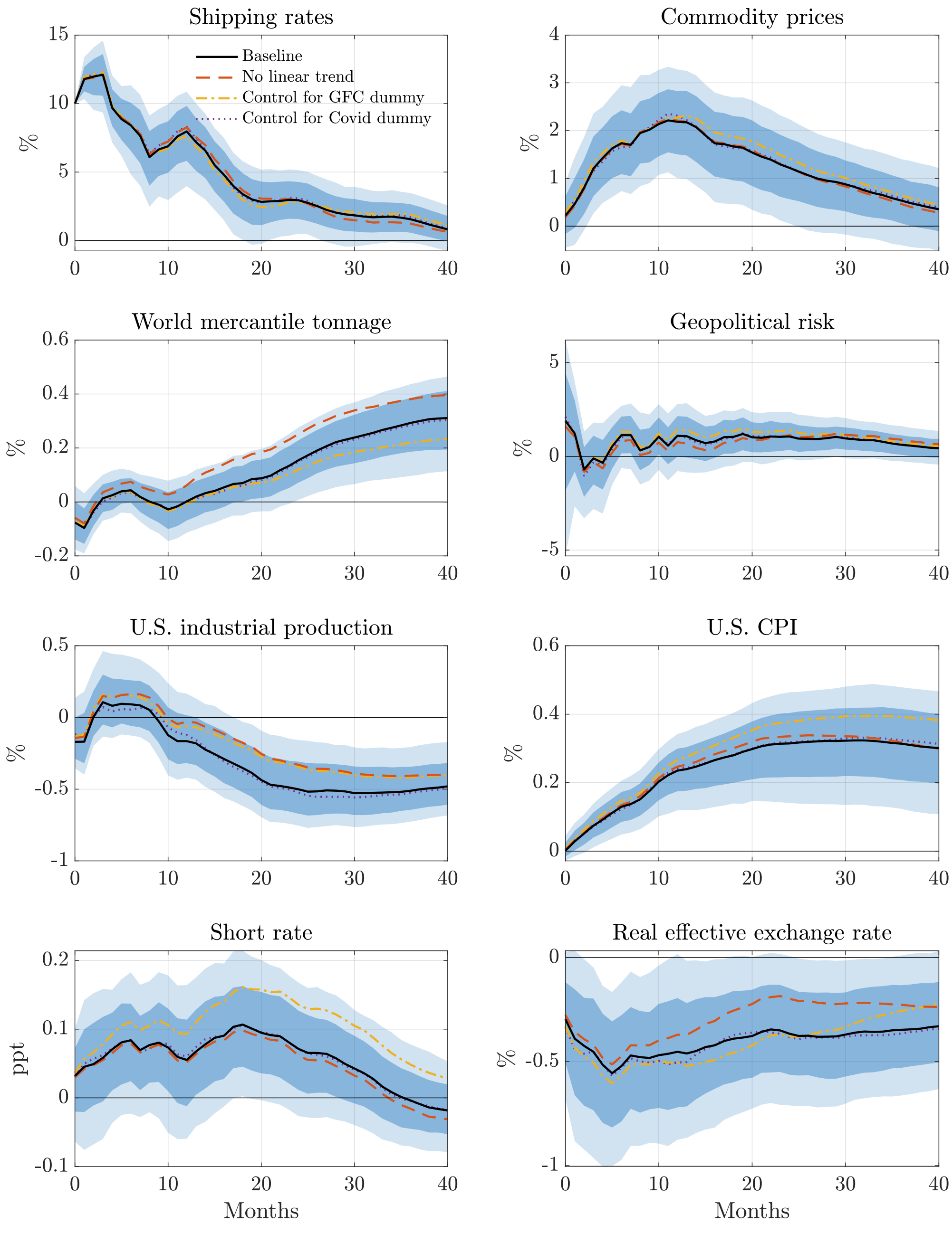
Notes: Impulse responses to a supply chain shock using the raw instrument. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.10: Sensitivity With Respect to Lag Order



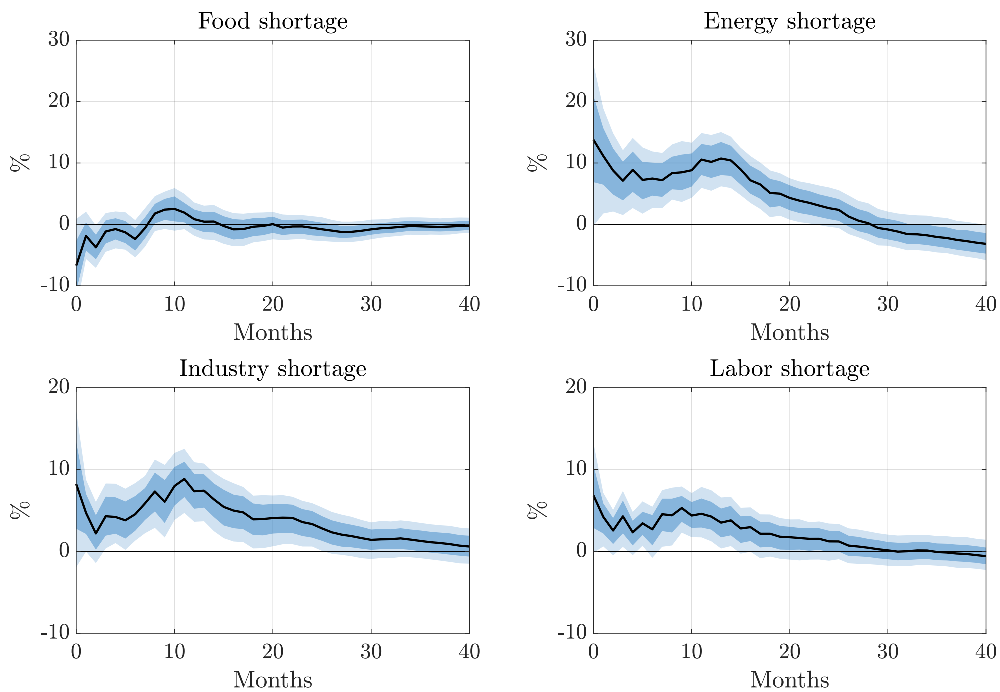
Notes: Impulse responses to a shipping cost shock with varying lag order. The lines are the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.11: Sensitivity With Respect to Deterministics



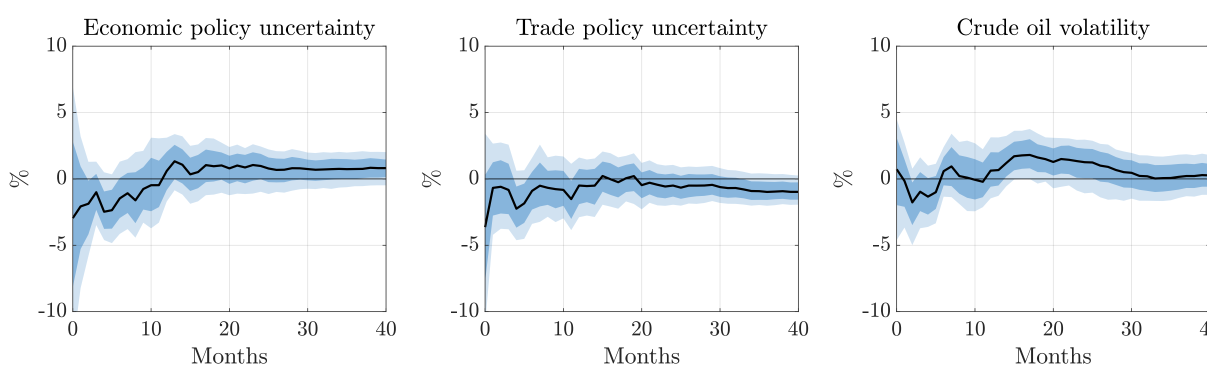
Notes: Impulse responses to a shipping cost shock using a model that excludes the linear trend and controls for the global financial crisis (GFC) and Covid-19 using a dummy variable. The lines are the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure D.1: Impacts on Shortage Measures



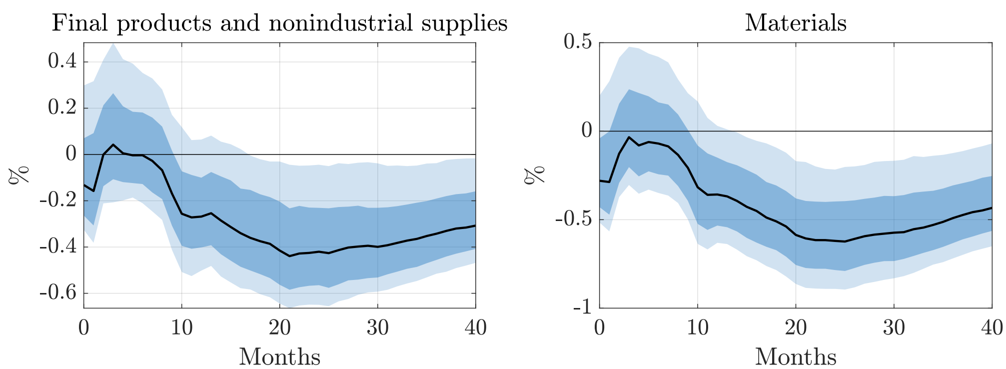
Notes: Impulse responses to a shipping cost shock, normalized to increase real shipping costs by 10 percent on impact. The IRFs are obtained by using our baseline VAR and augmenting it by the variable of interest. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent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

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.

Figure D.3: Impact on Industrial Production



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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