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. The persistently elevated shipping costs also lead to a sluggish expansion of the world merchant fleet, a significant increase in measures of supply chain shortages but are not associated with changes in geopolitical risk, consistent with our interpretation of exogenous supply chain disruptions. We use our estimates to discipline a network model of the U.S. economy and estimate key input elasticities.

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 choke points. The most important choke points are the Suez Canal and the Panama Canal. We perform a comprehensive narrative account on 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. This allows us to identify a structural supply chain shock using the shipping cost surprises as an instrument in a VAR model of the global economy.

An adverse supply chain shock leads to a strong, persistent increase in shipping rates that persists for months beyond the initial event. Even short-lived disruptions can trigger ripple effects that persist for months, as ship rerouting reduces capacity, creates bottlenecks, and disrupts the global shipping network. The increase in shipping costs has important consequences for the global economy. Producer prices for commodities increase significantly, albeit with some lag. The higher costs put pressure on the economy, and world industrial production starts to fall about a year after the shock. At the same time, the elevated shipping costs create an incentive to expand shipping supply, as can be seen from the sluggish increase in the world merchant fleet.

The effects on the U.S. turn out to be even more pronounced, likely reflecting the fact that the U.S. economy is particularly interconnected globally. U.S. industrial production falls significantly and persistently, the stock market falls 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 one-year rate, which tends to increase but the response is not significant. Quantitatively, a shock increasing

shipping rates by 10 percent leads to an increase in commodity prices by about 2 percent, a fall in world industrial production of 0.25 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 0.2 percent and the S&P 500 loses close to 2 percent.

The effect on inflation is fairly persistent, supporting the notion that supply chain disruptions have played an important role in the recent inflationary episode. We also document considerable heterogeneity in the price impacts across different categories.

To strengthen our interpretation of a supply chain shock, we look at the responses of a number of additional indicators. Reassuringly, we find that supply chain shocks lead to a significant increase in supply chain shortages, as proxied by newspaper-based shortage indicators. The sluggish increase in commodity prices together with the delayed increase in the world merchant fleet also suggests that we are not merely picking up commodity price shocks such as oil price shocks. Finally, we find that the shock has no significant impact on geopolitical risk. This is comforting because while geopolitical tensions can lead to significant disruptions in shipping, particularly in the Suez Canal, they are likely not independent of economic developments.

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, relaxing the assumption invertibility based an internal instruments approach produces very similar results.

Based on our new empirical evidence, we plan to discipline a network model of the U.S. economy and study the transmission of supply chain disruptions through the network. Specifically, we plan to estimate the elasticity of substitution between materials and capital/labor as well as the inner elasticities within the materials bundle, using our empirical responses of wages, aggregate and disaggregate input prices as targets. A key focus in our model is on dynamics, which will allow us to assess the extent of substitution possibilities in supply chains for critical products in the short run and in the longer term. With the estimated model at hand, we also plan to perform counterfactual analyses, to shed light on how policy can stabilize supply chain disruptions and improve the resilience of supply chains in critical industries.

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 witnessed unprecedented supply chain disruptions, exacerbated by climate change, which continues to strain fragile global networks. These challenges are especially acute in critical industries, making it essential to better under-

stand how to enhance resilience and adaptability.

A recent empirical literature studies the effects of supply chain pressures and shipping costs on the macroeconomy (Herriford et al., 2016; Jacks and Stuermer, 2021; Carrière-Swallow et al., 2023, among others). A number of studies 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. We contribute to this literature by developing a new identification strategy that leverages plausibly exogenous variation in shipping costs.

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. Our paper provides new evidence on both the broad-based, aggregate and granular, disaggregated economic impacts of supply chain disruptions.

On the theoretical side, we aim to provide new estimates for key parameters, such as the elasticities of substitution, in a state-of-the-art network model of the U.S. economy. In that sense, we will also contribute to an influential theoretical literature that studies how supply chain disruptions propagate through production networks and can have large aggregate impacts (Carvalho and Tahbaz-Salehi, 2019; Acemoglu, Akcigit, and Kerr, 2016; Acemoglu and Tahbaz-Salehi, 2024; Baqaee and Farhi, 2019, among others). To date, we still have a limited understanding of 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 La'O and Tahbaz-Salehi (2022); Rubbo (2023); Afrouzi and Bhattarai (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. This is a gap that this paper aims to fill.

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 preview our network model that we will use to estimate key elasticities and perform counterfactual analyses. Section 6 concludes.

2. Identification Strategy

Shipping costs are affected by a myriad of factors including global demand and supply pressures. This complicates the identification of a supply chain shock based on shipping price movements. Our identification strategy leverages the reliance of global supply chains on critical choke points and 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.

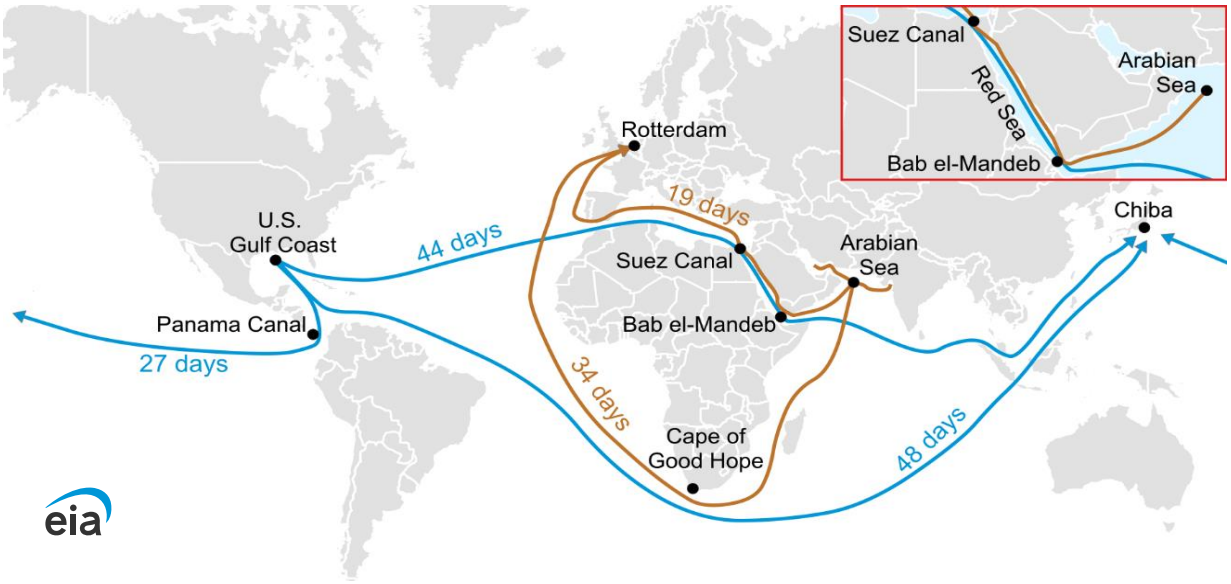
2.1. Choke Points in Global Supply Chains

Global supply chains are heavily reliant on maritime trade, which facilitates the movement of goods across vast distances at a relatively low cost. Over 80 percent of the world's trade by volume is transported by sea, making shipping routes critical to the functioning of international commerce. To facilitate the efficient movement of goods, commercial shipping depends on strategic trade routes. These waterways accommodate thousands of vessels annually; however, navigation is not always straightforward. Figure 1 displays the main global sea trade routes together with associated shipping times. A key feature of global shipping markets is the crucial dependence on certain critical points, known as maritime choke points.

Maritime choke points are 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 implications to supply chains globally. Two of the most critical choke points are the Suez Canal and the Panama Canal, which we focus on in this paper. Our idea is to construct a narrative account of disruptions at these choke points that are plausibly exogenous to the global economy.

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 1). Over 15 percent of international maritime trade passes through the Suez Canal, rendering international trade highly vulnerable to disruptions in the Suez Canal.

Figure 1: 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, from vessel groundings and collisions to fires, piracy incidents, and adverse weather conditions. 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, the most serious closure of the strategic water-

> way for almost 30 years, shipping sources said.
>
> 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.

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 1). Over 5 percent of international maritime trade passes through the Panama Canal.

Similar to the Suez Canal, throughout its history, the Panama Canal has experienced numerous disruptions to shipping traffic, from adverse weather conditions and fires to vessel groundings and collisions. Notably, in the recent years, the shipping traffic through the Panama Canal has 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 (Reuters, 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 (ACP) said.
>
> The change could affect about 20 percent of ships that use this route, ACP records show. (...)

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 detailed narrative account of events that disrupted shipping traffic through the Suez and the Panama Canal. For the Suez Canal, there is unfortunately no official archive documenting disruptions to the canal. Therefore, we rely on newspaper coverage, searching for events that disrupted traffic in the canal, such as collisions, groundings, or storms. For the panama canal, we rely on the official shipping advisories to identify draft restrictions. We confirm the salience of these restrictions based on newspaper archives.

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

Our 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. An overview of the events in our dataset is provided in Table 1. The events in the Suez 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 the events, we put great care to ensure that they are plausibly exogenous to the global economy. Thus, while we include vessel groundings, vessel collisions, fires, piracy incidents, and adverse weather conditions that are plausibly exogenous to economic activity, we for instance exclude events related to geopolitical tensions in the Middle East. Some of the events, such as restrictions due to adverse weather may be forecastable to a certain extent. In these cases, it is important to isolate the unanticipated

component of these events.

2.3. High-frequency Identification

We have identified a comprehensive list of events that disrupted key parts of global supply chains and are plausibly exogenous to the global economy. To measure the economic relevance of these events, we rely on high-frequency data on shipping rates. Our approach will also net out any anticipatory effects. 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 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 London-based Baltic Exchange's Baltic Dry Index (BDI), a composite of dry bulk timecharter averages, to measure global shipping costs. The index, issued daily, is a weighted average of three sub-indices that measure shipping costs across different vessel sizes: Baltic Capesize Index (40 percent), Baltic Panamax Index (30 percent), and Baltic Supramax Index (30 percent). Since each sub-index consists of timecharter averages across a range of global sea trade routes, the BDI is a comprehensive measure of global shipping costs. As a well-known barometer of maritime trade, it is closely monitored by market participants.

Construction of the instrument. We construct a series of shipping cost surprises by looking at how shipping costs change around the disruptive events that we identified. Specifically, we measure the surprises as the percentage change in the shipping costs on

the event reporting day compared to the last trading day before the event:[1]

$$SCSurprise_{t,d} = \frac{P^{\text{BDI}}_{t,d} - P^{BDI}_{t,d-1}}{P^{\text{BDI}}_{t,d-1}}, \tag{1}$$

where d and t indicate the day and month of the event, respectively, and $P^{\text{BDI}}_{t,d}$ 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 2: Shipping Cost Surprise Series

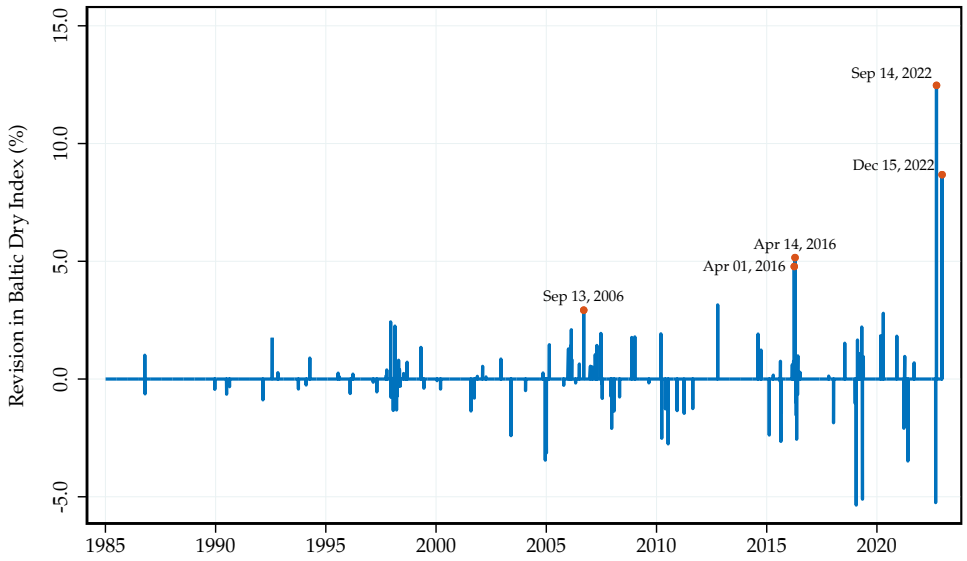


Figure 2 shows the shipping cost surprise series at the daily frequency. Events that disrupt shipping traffic can have a significant impact on shipping costs, with several events moving shipping costs in excess of 3 percent. For instance, on September 13, 2006, an Egyptian dredger sank in the Suez Canal, 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. 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 September 14, 2022, reporting of a rare overflow at the Panama Canal's Gatun Locks, that temporarily

[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.

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. Note that there are also a number of events associated with negative shipping cost surprises. This can happen when news signal that a disruption is less severe than previously expected.

Because our outcome variables of interest are only available at the monthly frequency, we aggregate these daily surprises, $SCSurprise_{t,d}$, to a monthly series, $SCSurprise_t$. Following Gertler and Karadi (2015), we first cumulate surprises on all events days to obtain a daily cumulative surprise series. Second, we take monthly averages of the daily cumulative surprise series. Finally, we first difference the series to obtain the monthly average surprise series. By construction, in months without any events, the surprise series takes zero value. Note that this procedure is equivalent to weighting a surprise for an event 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 of 1% occurs on the 7th calendar day of a month with 30 days, 0.8% of the surprise will be assigned to the current month and 0.2% of the surprise will be assigned to the next month. Since this approach of temporal aggregation has been known to cause additional serial correlation, we purge the surprise series of serial correlation by regressing on its lags and using the residual, as suggested by Miranda-Agrippino and Ricco (2021).

Construction choices and diagnostics. 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 0.72. 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 0.83. The only exception is shipping rates, which individually help predict the surprises somewhat. However, removing this predictability by purging our surprises by shipping rates yields very similar results. 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 C.

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. For efficiency reasons, we rely on VAR techniques for estimation (Li, Plagborg-Møller, and Wolf, 2024). For identification, we use the external instrument approach (Stock, 2008; Stock and Watson, 2012; Mertens and Ravn, 2013). While this approach tends to be quite efficient, it provides biased estimates if the VAR is not invertible. Thus, we also present results from an internal instrument approach (Ramey, 2011; Plagborg-Møller and Wolf, 2019), which includes the instrument in the VAR and is robust to problems of non-invertibility.

3.1. Framework

Our starting point is the standard VAR model:

$$\mathbf{y}_t = \mathbf{b} + \mathbf{B}_1\mathbf{y}_{t-1} + \cdots + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{u}_t, \tag{2}$$

where p is the lag order, $\mathbf{y}_t$ is a $n \times 1$ vector of endogenous variables, $\mathbf{u}_t$ is a $n \times 1$ vector of reduced-form innovations with covariance matrix $\text{Var}(\mathbf{u}_t) = \mathbf{\Sigma}$, $\mathbf{b}$ is a $n \times 1$ vector of constants, and $\mathbf{B}_1, \ldots, \mathbf{B}_p$ are $n \times n$ coefficient matrices.

Under the assumption that the VAR is invertible, we can write the innovations $\mathbf{u}_t$ as linear combinations of the structural shocks $\boldsymbol{\varepsilon}_t$:

$$\mathbf{u}_t = \mathbf{S}\boldsymbol{\varepsilon}_t. \tag{3}$$

By definition, the structural shocks are mutually uncorrelated, i.e. $\text{Var}(\boldsymbol{\varepsilon}_t) = \mathbf{\Omega}$ is diagonal. From the invertibility assumption (3), we get the standard covariance restrictions $\mathbf{\Sigma} = \mathbf{S\Omega S}'$.

We are interested in characterizing 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

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:

$$\mathbb{E}[z_t \varepsilon_{1,t}] = \alpha \neq 0 \tag{4}$$

$$\mathbb{E}[z_t \boldsymbol{\varepsilon}_{2:n,t}] = \mathbf{0}, \tag{5}$$

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 (4) is the relevance requirement and assumption (5) is the exogeneity condition. These assumptions identify the structural impact vector $\mathbf{s}_1$ up to sign and scale:

$$\mathbf{s}_1 \equiv \boldsymbol{\theta}_0 \propto \frac{\mathbb{E}[z_t \mathbf{u}_t]}{\mathbb{E}[z_t \mathrm{u}_{1,t}]}, \tag{6}$$

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; a lead-lag exogeneity condition $\mathbb{E}[z_t \boldsymbol{\varepsilon}_{t+j}] = \mathbf{0}$ for $j \neq 0$ suffices. Invertibility is only required for the dynamic effects beyond impact.

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).

Local projections. The VAR approach tends to be efficient, 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.

To assess how restrictive these assumptions are, we estimate the responses to a supply chain shock using local projections à la Jordà (2005). Specifically, we perform two exercises. The first is to estimate the dynamic responses given the impact effect $\boldsymbol{\theta}_0$. This

amounts to directly estimating the reduced-form responses $\boldsymbol{\psi}_0^h$:

$$\mathbf{y}_{t+h} = \mathbf{b} + \boldsymbol{\psi}_0^h \mathbf{y}_t + \cdots + \boldsymbol{\psi}_p^h \mathbf{y}_{t-p} + \mathbf{u}_{t+h}, \tag{7}$$

and computing the structural responses as $\boldsymbol{\theta}_h = \boldsymbol{\psi}_0^h \boldsymbol{\theta}_0$. This approach relaxes the invertibility requirement and the dynamic VAR structure but is less demanding than the local projections-instrumental variable estimator (Jordà, Schularick, and Taylor, 2015). Instead, it crucially relies on the lead-lag exogeneity restriction outlined above.

To assess the extent of lag truncation bias, we alternatively estimate the impulse responses to the supply chain VAR shock using local projections. To fix ideas, we first extract the supply chain shock from the monthly VAR as $\varepsilon_{1,t} = \mathbf{s}_1' \boldsymbol{\Sigma}^{-1} \mathbf{u}_t$ (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:

$$y_{i,t+h} = \alpha_{h,0}^i + \theta_h^i \varepsilon_{1,t} + \beta_{h,1}^i y_{i,t-1} + \ldots + \beta_{h,p}^i y_{i,t-p} + \xi_{i,t,h}, \tag{8}$$

where ψ_h^i is the effect on variable i at horizon h. This approach assumes (partial) invertibility, but relaxes the dynamic VAR structure, directly estimating the impulse responses to the shock of interest. Because we estimate the dynamic causal effects directly without extrapolating from the first autocovariances, the approach is less subject to lag truncation bias.

An additional appeal of this approach is that it allows to estimate the effects on variables that are only available at a lower frequency, such as on a quarterly or even annual basis. In this case, we aggregate the shock $\varepsilon_{1,t}$ by summing over the respective months before running the local projections. This mitigates the problem that external 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 consists of 9 variables, consisting of a global supply chain block, which includes the real shipping cost (measured using the BDI), real producer price index, world industrial production, and world merchant fleet and a block for the U.S. economy, which includes U.S. industrial production, consumer price index (CPI), the S&P 500, and the one-year treasury yield.[2] Detailed information on

[2]Unfortunately, world merchant fleet 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.

the data, including sources, can be found in Appendix A.

We use monthly data spanning the period 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. 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.

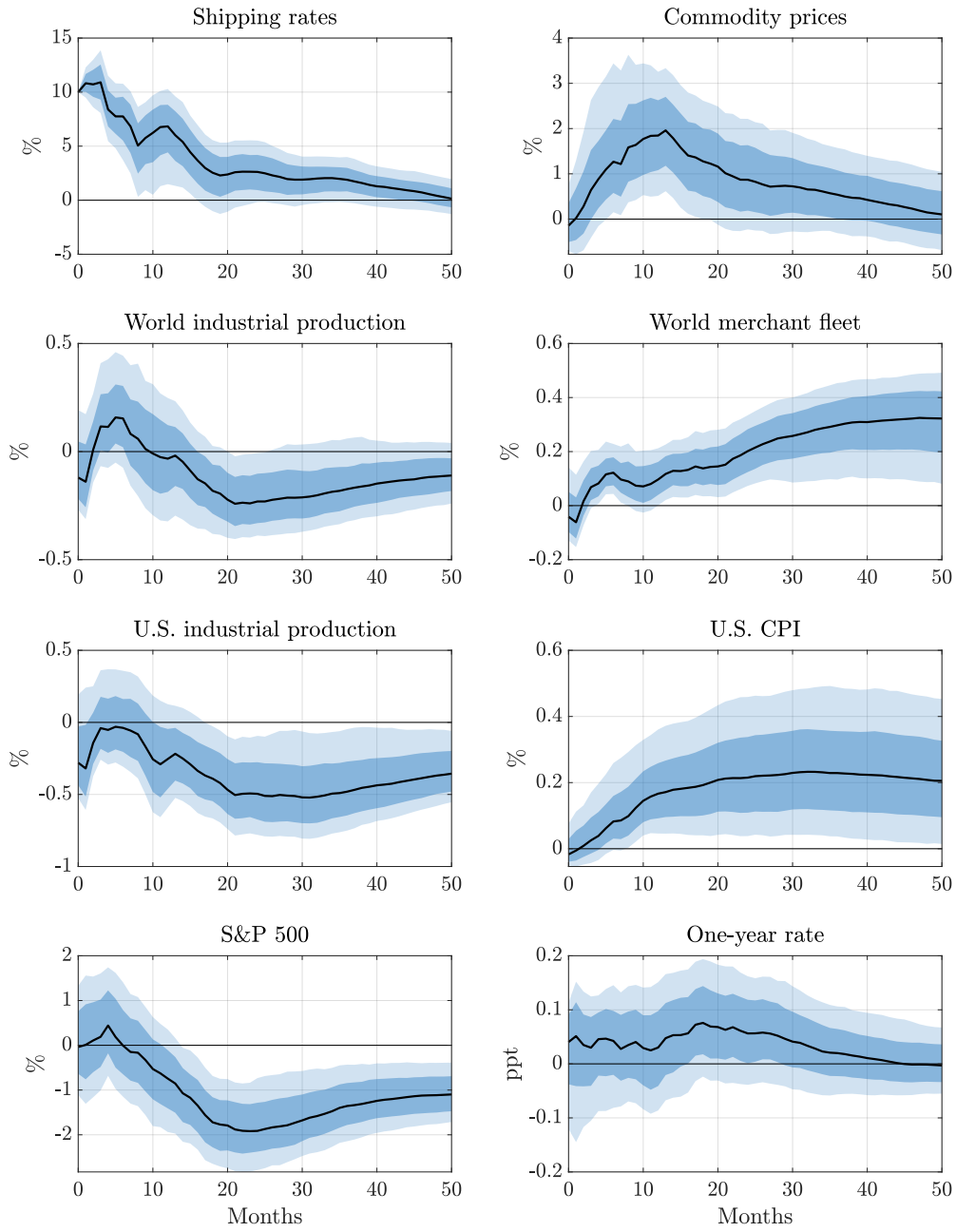
First stage. The main identifying assumption behind the external instruments approach is that the instrument is correlated with the structural shock of interest but uncorrelated with all other structural shocks. This assumption is not testable, but we select the disruptions underlying our surprise series 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 costs surprise series is a strong instrument, with a heteroskedasticity-robust F-statistic of 21.43. As this is above conventional critical values, the instrument appears to be sufficiently strong to conduct standard inference.

Macroeconomic effects. Figure 3 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 disruptive events we use in our instrument themselves. 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 re-routed, which reduces available capacity for scheduled shipments,

Figure 3: Impulse Responses to a Supply Chain Shock



First stage: Robust F-statistic: 21.43, R^2: 3.32%, Adjusted R^2: 3.16%

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

creates bottlenecks at alternative ports, and disrupts the carefully orchestrated 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 for the global economy. Producer input prices for commodities increase significantly, albeit only with some lag. The higher costs put pressure on the economy, and world industrial production starts to fall about a year after the shock. At the same time, the elevated shipping costs create an incentive to expand shipping supply, as can be seen from the sluggish increase in the size of the world merchant fleet.

The effects on the U.S. turn out to be even more pronounced, likely reflecting the fact that the U.S. economy is particularly interconnected. U.S. industrial production falls significantly and persistently, the stock market falls, 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 one-year rate, which tends to increase but the response is not statistically significant.

Quantitatively, a shock increasing shipping rates by 10 percent leads to an increase in commodity prices by about 2 percent, a fall in world industrial production of 0.25 percent, and an increase in the world merchant fleet by 0.3 percent, at the peak. U.S. industrial production falls by around 0.5 percent, the U.S CPI increases by 0.2 percent, and the S&P 500 loses close to 2 percent. These impacts are substantial and comparable with the economic impacts of other supply-side shocks, such as commodity price shocks (Kilian, 2009; Baumeister and Hamilton, 2019; Känzig, 2021).

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 economic impacts.

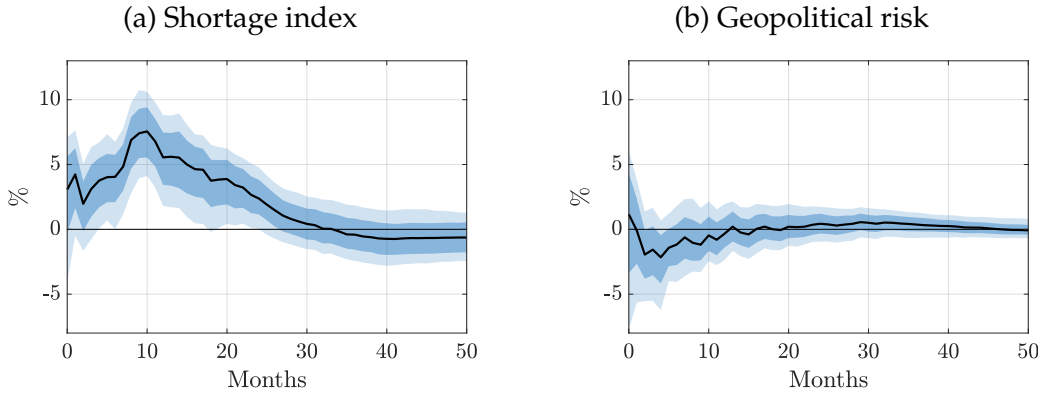
4.1. Wider Effects and Propagation Channels

To strengthen our interpretation of a supply chain shock, we study the effects of the shock on a wider range of macroeconomic variables. To compute the impulse responses for additional monthly variables, we employ a marginal VAR approach, augmenting the baseline VAR by one variable at a time as in Gertler and Karadi (2015). For variables at lower frequencies, we extract an estimate of the supply chaing shock from the VAR, aggregate it and estimate the lower-frequency responses using local projections, as explained in Section 3.1.

Shortages. To corroborate our interpretation of a supply chain shock, we assess whether the shock is associated with significant shortages. To that end, we rely on the newspaper-based indicator of supply chain shortages, constructed by Caldara, Iacoviello, and Yu, 2024. From Figure 4a, we can see that the supply chain shock leads to a significant increase in supply chain shortages, consistent with the notion that supply chain disruptions causing higher costs of shipping eventually translate into input shortages. Looking into the components of the shortage index in Figure C.6, we find that shortages are particularly pronounced for industrial materials and energy, which is expected given that bulk carriers and oil tankers form majority of the world fleet capacity.

Geopolitical risk. Given the significant impact on energy shortages, one may be concerned that we primarily capture geopolitical oil supply risk. Particularly, shipping in the Suez canal can be substantially affected by geopolitical developments in the region. Such geopolitical tensions, however, are often not independent of economic developments and may threaten our identifying assumptions. In selecting our events, we thus put great care into excluding disruptions associated with geopolitical tensions. Reassuringly, we confirm that our identified supply chain shock has no significant effect on geopolitical risk, see Figure 4b. 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 C.7 in the appendix).

Figure 4: Effects on Supply Chain Shortages and Geopolitical Risk



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 solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

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 5a, 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.

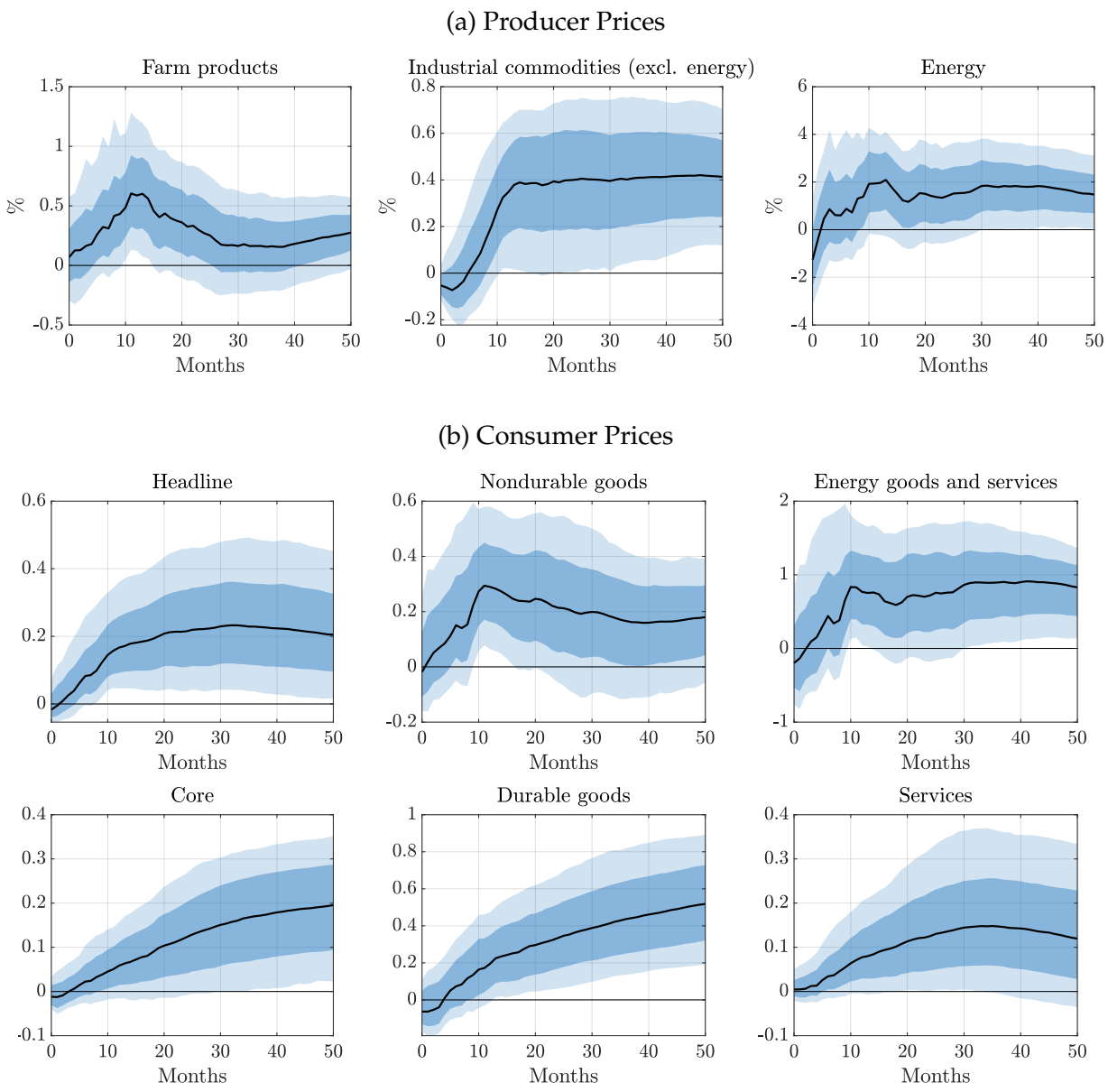
The increases in the producer prices are passed onto to consumers, although the pass-through appears to be not complete. In Figure 5b, we show the responses of major consumer price components, including core, nondurable, energy, durable, and service prices, alongside the headline measure from our baseline 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 significanlty, with the durable price response showing 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 translates into higher inflation expectations. Figure 6 shows the inflation expectations for consumers from the Michigan survey. We can see that inflation expectations increase persistently, even though the magnitude is not that high.

Economic activity. Shipping disruptions delay the transport essential industrial materials, raising costs for manufacturers. In Figure 7a, we can see that output and employment in manufacturing falls considerably. Interestingly, the shock does not seem to have significant effects on real wages.

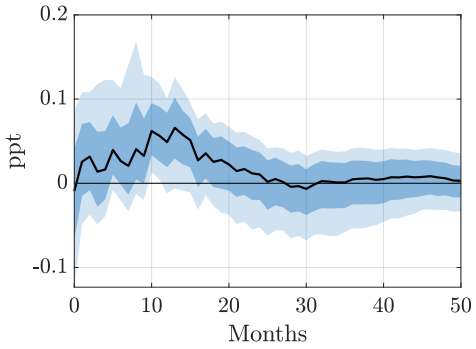
The substantial impacts on industrial production and manufacturing in particular translates into more broad based economic effects. Figure 7b shows the responses of real GDP, private investment and consumption. A supply chain shock leads to a fall in

Figure 5: 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 solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure 6: Consumer 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 solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

output and its components. At peak, real GDP falls by about 0.25 percent, investment by 1 percent, and consumption by 0.2 percent.

Trade. Supply chain shocks also have significant effects on trade. Following a disruption, we expect imports to decrease mechanically, at least in the short run. In the medium run, imports may fall by even more given the adverse impacts of the shock on economic activity. This is indeed what we find. Figure 8 shows the responses of imports and import prices. In line with the commodity price response, we find that import prices also increase significantly, albeit also only with a lag. Imports fall substantially on impact and the effect tends to build up over time.

4.2. Sensitivity

In this section, we perform a comprehensive series of sensitivity checks. Our results are robust along a number of dimensions, including the identification strategy, estimation strategy, and model specification.

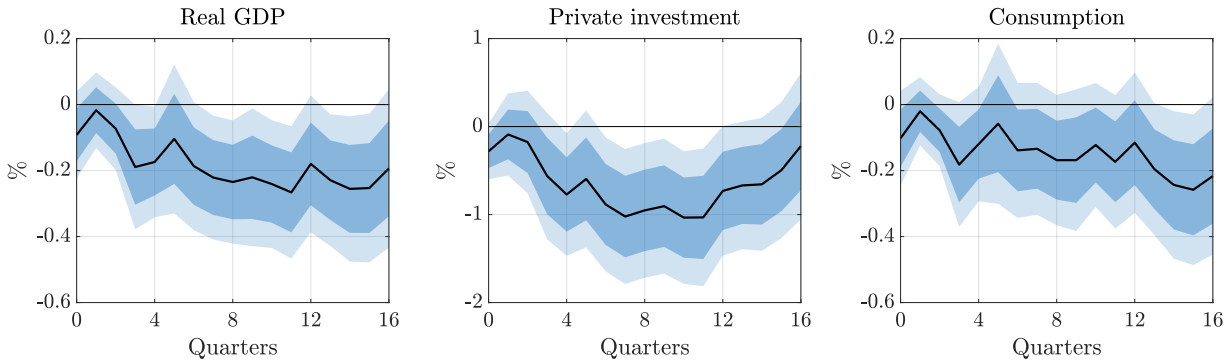
Identification strategy. Grounding and collisions, which constitute the majority of the events we identify for the Suez Canal, are arguably unanticipated. However, adverse weather-related draft restrictions in the Panama Canal may be susceptible to some anticipatory effects. The high-frequency approach we employ nets out such anticipatory effects. To further alleviate concerns about anticipation, we construct a more stringent version of our baseline instrument, excluding events that could potentially have anticipatory effects. For instance, in periods of prolonged adverse weather conditions such as

Figure 7: Impact on Economic Activity

(a) Manufacturing Sector

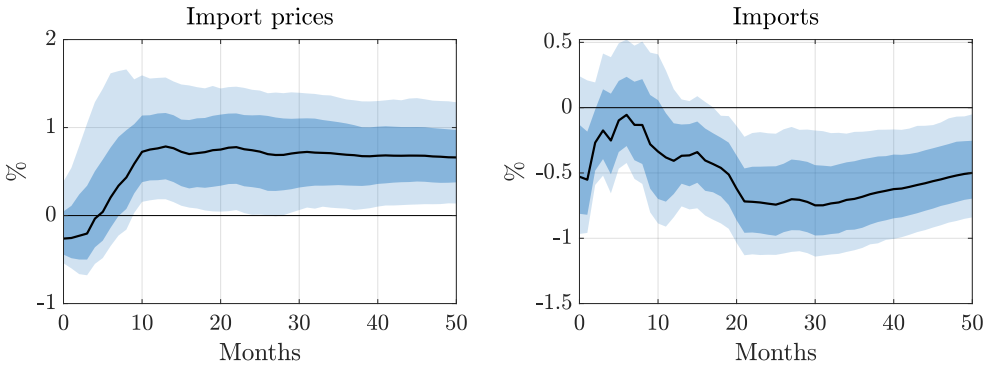


(b) Broader Impacts



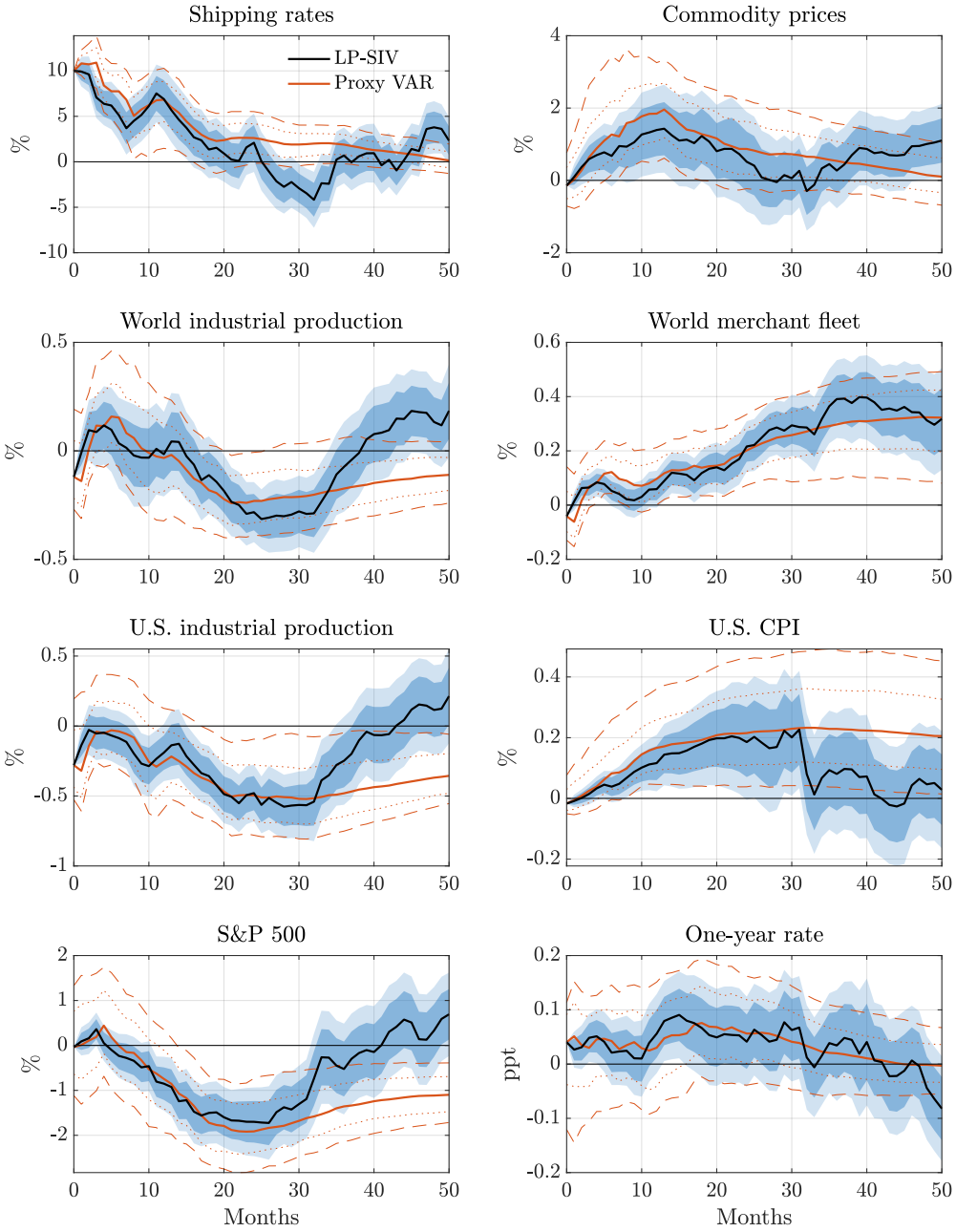
Notes: Impulse responses to a supply chain shock, normalized to increase real shipping costs by 10 percent on impact. The IRFs in Panel (a) are obtained by using our baseline VAR and augmenting it by the variable of interest. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively. The IRFs in Panel (b) are estimated by local projections (8) on the aggregated supply chain shock extracted from our baseline external instruments VAR.

Figure 8: Impact on Imports



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 solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure 9: Impulse Responses to a supply chain shock, Local Projections



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

the El Nino, we include only the first draft restriction. As shown in Figure C.1, the results obtained with a more restrictive set of events mirror those using our baseline instrument, but are slightly less precise due to the lower number of events. Furthermore, we verify that our results are not influenced by the method used to aggregate daily surprises into monthly surprises, see Figure C.2 in the appendix.

Estimation strategy. We assess how restrictive the VAR assumptions are via two exercises. First, we assess the extent of lag truncation bias, retaining the invertbility requirement. To that end, we estimate the responses using local projections on the shock identified from the VAR. The responses turn out to be very similar to our baseline responses, with only commodity price response being slightly muted (see Figure C.3 in the appendix). These results suggest that our dynamic VAR structure is flexible enough to capture the U.S. macroeconomic dynamics adequately.

Second, we further relax the invertibility requirement. To this end, we estimate local projections using the relative structural impact vector following Jordà (2005), which imposes a limited lead lag exogeneity requirement instead. Reassuringly, the results turn out to be again very similar to the baseline responses based on the external instruments approach. Figure 9 shows that the results are virtually identical, up until medium horizons. At longer horizons, some responses are less persistently estimated.

Model specification. We also study the sensitivity with respect to some additional modeling choices. Specifically, the results turn out to be robust to the lag order (see Figure C.4) and deterministics (see Figure C.5).

5. A Network Model of the U.S. Economy

Until now, we have documented new empirical facts on the broad-based, aggregate and granular, disaggregated economic impacts of supply chain disruptions.

In this section, we want to leverage this evidence to shed light on the degree of substitutability between key input factors in the U.S. economy. We plan to use our empirical evidence to discipline a network model of the U.S. economy and study the transmission of supply chain disruptions through the network. Specifically, we want to provide new estimates for key parameters: the elasticities of substitution between materials, capital and labor, as well as the elasticities of substitution within the inner material bundle—both in the aggregate and across sectors, and in the short and long run. We provide a sketch of the exercise here, but will have a full working model by the summer.

At the core of the model lies the following CES production function. We assume that firm i in industry n uses the following technology:

$$F_{nit}\left(K_{nit}, L_{nit}, M_{nit}\right) \propto \left(\left[\left(A_{nit}K_{nit}\right)^{\frac{\sigma_n - 1}{\sigma_n}} + \left(B_{nit}L_{nit}\right)^{\frac{\sigma_n - 1}{\sigma_n}} \right]^{\frac{\sigma_n}{\sigma_n - 1}\frac{\zeta_n - 1}{\zeta_n}} + \left(C_{nit}M_{nit}\right)^{\frac{\zeta_n - 1}{\zeta_n}} \right)^{\frac{\zeta_n}{\zeta_n - 1}} \tag{9}$$

where σ_n is the elasticity of substitution between capital K and labor L and ζ_n is the elasticity of substitution between materials M and its capital-labor bundle.

To be able to shed light on the short- and long-run elasticities, we assume adjustment costs for the key inputs: capital, labor and materials. The remainder of the model is standard. As an example, the short-run elasticity for labor and materials is given by (assuming $\sigma_n = 1$):

$$\zeta_{n,\text{SR}} = \frac{\partial \ln\left(L_{nit}/M_{nit}\right)}{\partial \ln\left(P_{Mt}/W_t\right)}. \tag{10}$$

The long-run elasticity will converge to ζ_n as the adjustment costs vanish.

The key idea is then to estimate the model using impulse response matching. Specifically, we want to use the impulse responses on wages relative to the price of capital, the responses of wages relative to aggregate input prices, and the responses to relative input prices, to estimate the long-run elasticities of substitution and adjustment cost parameters.

The estimated elasticities will be of great use to identify vulnerabilities in U.S. supply chains. With the estimated model at hand, we also plan to perform counterfactual analyses, shedding light on how to stabilize supply chain disruptions and how to improve the resilience of supply chains in the longer term.

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 such as the Suez and Panama Canals. By leveraging plausibly exogenous disruptive events at these locations and utilizing high-frequency financial data, we identify structural supply chain shocks and their cascading effects on the global economy. Our findings demonstrate that disruptive supply chain shocks can have pervasive economic effects. Such shocks lead to persistent increases in shipping rates, commodity prices, and consumer prices, while

negatively impacting industrial production and stock market performance. These effects are particularly pronounced in highly interconnected economies like the United States, creating stagflationary pressures and posing challenges for monetary policy. We plan to study these policy trade-offs in more detail in a network model of the global economy.

Overall, our results underscore the fragility of global supply chains and their significant impact on macroeconomic outcomes. The estimated, persistent inflationary effects support the notion that supply chain disruptions have played an important role in recent inflationary episodes. Our research contributes to a better understanding of the complex interplay between supply chain shocks and economic performance, providing valuable insights for policymakers and businesses alike. As the global economy continues to face uncertainties and potential disruptions, our findings emphasize the importance of building more resilient and adaptable supply chains to mitigate the risks associated with an increasingly interconnected world.

References

Acemoglu, Daron, Ufuk Akcigit, and William Kerr (2016). "Networks and the Macroeconomy: An Empirical Exploration". *NBER Macroeconomics Annual* 30, pp. 273–335.

Acemoglu, Daron and Alireza Tahbaz-Salehi (2024). "The Macroeconomics of Supply Chain Disruptions". *Review of Economic Studies*, rdae038.

Afrouzi, Hassan and Saroj Bhattarai (2023). *Inflation and gdp dynamics in production networks: A sufficient statistics approach*. Tech. rep. National Bureau of Economic Research.

Atalay, Enghin (2017). "How important are sectoral shocks?" *American Economic Journal: Macroeconomics* 9.4, pp. 254–280.

Bai, Xiwen, Jesús Fernández-Villaverde, Francesco Zanetti, and Yiliang Li (2024). "The Causal Effects of Global Supply Chain Disruptions on Macroeconomic Outcomes: Evidence and Theory". *Working Paper*.

Baqaee, David Rezza and Emmanuel Farhi (2019). "The Macroeconomic Impact of Microeconomic Shocks: Beyond Hulten's Theorem". *Econometrica* 87.4, pp. 1155–1203.

Baumeister, Christiane and James D. Hamilton (2019). "Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks". *American Economic Review* 109.5, pp. 1873–1910.

Benigno, Gianluca, Julian Di Giovanni, Jan J. Groen, and Adam I Noble (2022). "The GSCPI: A New Barometer of Global Supply Chain Pressures". *Federal Reserve Bank of New York Staff Reports* 1017.

Blaum, Joaquin, Federico Esposito, and Sebastian Heise (2023). *Input sourcing under supply chain risk: evidence from us manufacturing firms*. Tech. rep. Mimeo.

Caldara, Dario, Matteo Iacoviello, and David Yu (2024). "Measuring Shortages Since 1900". *Working Paper*.

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

Carvalho, Vasco M, Makoto Nirei, Yukiko U Saito, and Alireza Tahbaz-Salehi (2021). "Supply chain disruptions: Evidence from the great east japan earthquake". *The Quarterly Journal of Economics* 136.2, pp. 1255–1321.

Carvalho, Vasco M. and Alireza Tahbaz-Salehi (2019). "Production Networks: A Primer". *Annual Review of Economics* 11.1, pp. 635–663.

Castro-Vincenzi, Juanma, Gaurav Khanna, Nicolas Morales, and Nitya Pandalai-Nayar (2024). *Weathering the storm: Supply chains and climate risk*. Tech. rep. National Bureau of Economic Research.

Fernández-Villaverde, Jesús, Tomohide Mineyama, and Dongho Song (2024). "Are We Fragmented Yet? Measuring Geopolitical Fragmentation and its Causal Effects".

Gertler, Mark and Peter Karadi (2015). "Monetary policy surprises, credit costs, and economic activity". *American Economic Journal: Macroeconomics* 7.1, pp. 44–76.

Herriford, Trenton, Elizabeth M Johnson, Nicholas Sly, A Lee Smith, et al. (2016). "How does a rise in international shipping costs affect US inflation?" *Macro Bulletin. Federal Reserve Bank of Kansas City*, pp. 1–3.

Jacks, David S. and Martin Stuermer (2021). "Dry bulk shipping and the evolution of maritime transport costs, 1850–2020". *Australian Economic History Review* 61.2, pp. 204–227.

Jentsch, Carsten and Kurt G. Lunsford (2019). "The dynamic effects of personal and corporate income tax changes in the United States: Comment". *American Economic Review* 109.7, pp. 2655–78.

Jordà, Òscar (2005). "Estimation and inference of impulse responses by local projections". *American Economic Review* 95.1, pp. 161–182.

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor (2015). "Betting the house". *Journal of International Economics* 96, S2–S18.

Känzig, Diego R. (2021). "The macroeconomic effects of oil supply news: Evidence from OPEC announcements". *American Economic Review* 111.4, pp. 1092–1125.

Kilian, Lutz (2009). "Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market". *American Economic Review* 99.3, pp. 1053–1069.

La'O, Jennifer and Alireza Tahbaz-Salehi (2022). "Optimal monetary policy in production networks". *Econometrica* 90.3, pp. 1295–1336.

Li, Dake, Mikkel Plagborg-Møller, and Christian K Wolf (2024). "Local projections vs. vars: Lessons from thousands of dgps". *Journal of Econometrics* 244.2, p. 105722.

Mertens, Karel and Morten O. Ravn (2013). "The dynamic effects of personal and corporate income tax changes in the United States". *American Economic Review* 103.4, pp. 1212–47.

Minton, Robert and Brian Wheaton (2023). "Delayed Inflation in Supply Chains: Theory and Evidence". *Available at SSRN 4470302*.

Miranda-Agrippino, Silvia and Giovanni Ricco (2021). "The Transmission of Monetary Policy Shocks". *American Economic Journal: Macroeconomics* 13.3, pp. 74–107.

Montiel Olea, José L., James H. Stock, and Mark W. Watson (2016). "Uniform inference in SVARs identified with external instruments".

Nakamura, Emi and Jón Steinsson (2018). "High-frequency identification of monetary non-neutrality: The information effect". *The Quarterly Journal of Economics* 133.3, pp. 1283–1330.

Oberfield, Ezra and Devesh Raval (2021). "Micro data and macro technology". *Econometrica* 89.2, pp. 703–732.

Plagborg-Møller, Mikkel and Christian K. Wolf (2019). "Local projections and VARs estimate the same impulse responses".

Quilis, Enrique M. (2020). *Temporal disaggregation*. https://www.mathworks.com/matlabcentral/fileexchange/69800-temporal-disaggregation.

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

— (2011). "Identifying government spending shocks: It's all in the timing". *The Quarterly Journal of Economics* 126.1, pp. 1–50.

Reuters (2004). *Suez Canal blocked by tanker, vessels back up*.

— (2015). *Panama temporarily restricts draft of vessels in the canal*.

Rubbo, Elisa (2023). "Networks, Phillips curves, and monetary policy". *Econometrica* 91.4, pp. 1417–1455.

Sims, Christopher A., James H. Stock, and Mark W. Watson (1990). "Inference in linear time series models with some unit roots". *Econometrica*, pp. 113–144.

Stock, James H. (2008). "What's new in Econometrics: Time Series, lecture 7". *NBER Summer Institute Short Course Lectures*.

Stock, James H. and Mark W. Watson (2012). "Disentangling the channels of the 2007-2009 recession". *Brookings Papers on Economic Activity*.

— (2018). "Identification and estimation of dynamic causal effects in macroeconomics using external instruments". *The Economic Journal* 128.610, pp. 917–948.

U.S. Energy Information Administration (2024). *Red Sea attacks increase shipping times and freight rates*. https://www.eia.gov/todayinenergy/detail.php?id=61363.

Online Appendix

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

Diego R. Känzig[†]
Ramya Raghavan[‡]

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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.

Figure A.1: Transformed Data Series

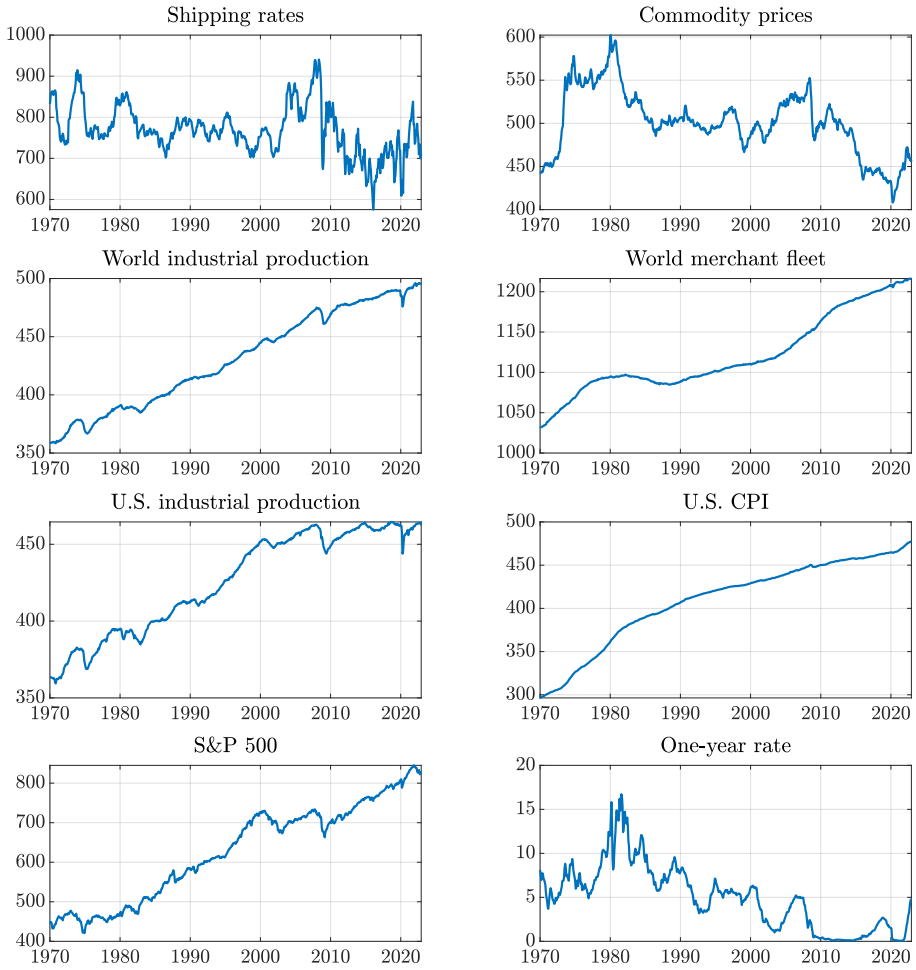


Table A.1: Data Description, Sources, and Coverage

Variable	Description	Source	Sample	Trans.
Instrument				
BDIY	Baltic dry index (monthly average), extended using Hamilton (2021)	Bloomberg	1970M1-2022M12	$100 \times \Delta \log$
Baseline				
BDIY	Baltic dry index (monthly average), extended using Hamilton (2021)	Bloomberg	1970M1-2022M12	$100 \times \log$
BCOM	Bloomberg commodity index (monthly average)	Bloomberg	1970M1-2022M12	$100 \times \log$
WORLDIP	Industrial production index for OECD countries and six major non-member economies (Brazil, China, India, Indonesia, Russia, and South Africa) from Baumeister and Hamilton (2019)	Baumeister's webpage	1970M1-2022M12	$100 \times \log$
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	1970M1-2022M12	$100 \times \log$
INDPRO	U.S. industrial production: total index (2017 = 100; seasonally adjusted)	FRED	1970M1-2022M12	$100 \times \log$
PCEPI	Personal consumption expenditures: chain-type price index (2017 = 100; seasonally adjusted)	FRED	1970M1-2022M12	$100 \times \log$
SPX	S&P 500 index (monthly average)	Bloomberg	1970M1-2022M12	$100 \times \log$
GS1	Market yield on U.S. treasury securities at 1-year constant maturity, quoted on an investment basis	FRED	1970M1-2022M12	Level
Additional Variables				
SHORTAGE	Shortage index from Caldara, Iacoviello, and Yu (2024)	Shortage index webpage	1970M1-2022M12	$100 \times \log$
GPR	Geopolitical risk index from Caldara and Iacoviello (2022)	GPR index webpage	1970M1-2022M12	$100 \times \log$

Figure B.1: Autocorrelation Function

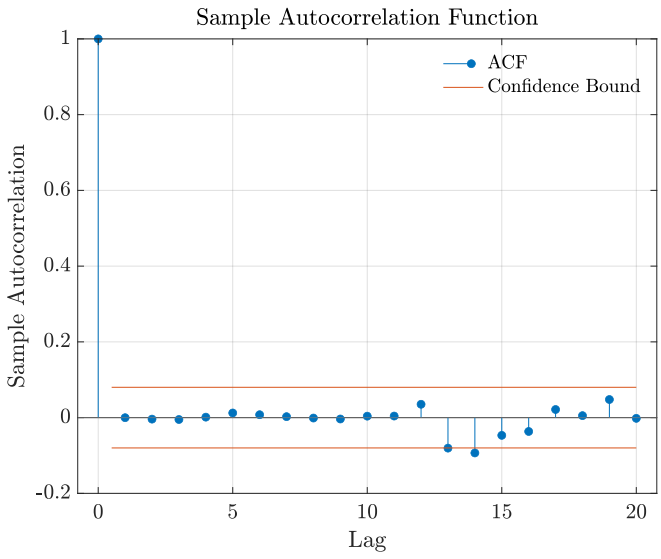


Table B.1: Granger Causality Tests

Variable	p-value
Instrument	0.9959
Shipping rates	0.1204
Commodity prices	0.6117
World industrial production	0.7709
World merchant fleet	0.8108
U.S. industrial production	0.4239
U.S. CPI	0.6462
S&P 500	0.7987
One-year rate	0.5426
Oil price	0.8747
Geopolitical risk	0.6000
VXO	0.8857
Shortage index	0.7378
Joint	0.5824

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.

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.

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	-0.01	0.82	396	1985M01-2017M12
Oil supply	Kilian, 2008	-0.05	0.48	237	1985M01-2004M09
	Caldara, Cavallo, and Iacoviello, 2019	-0.03	0.61	372	1985M01-2015M12
	Baumeister and Hamilton, 2019	0.03	0.55	456	1985M01-2022M12
	Kilian, 2009	-0.05	0.37	276	1985M01-2007M12
Global demand	Kilian, 2009	0.11	0.06	276	1985M01-2007M12
Oil-specific demand	Kilian, 2009	-0.07	0.27	276	1985M01-2007M12
Oil supply news	Känzig, 2021	-0.05	0.33	456	1985M01-2022M12
Panel B: Productivity Shocks					
Productivity	Basu, Fernald, and Kimball, 2006	-0.02	0.86	108	1985Q1-2011Q4
	Smets and Wouters, 2007	-0.06	0.59	80	1985Q1-2004Q4
Panel C: News shocks					
News	Barsky and Sims, 2011	-0.17	0.11	91	1985Q1-2007Q3
	Kurmann and Otrok, 2013	0.06	0.62	82	1985Q1-2005Q2
	Beaudry and Portier, 2014	-0.02	0.82	111	1985Q1-2012Q3
Panel D: Monetary policy					
Monetary policy	Bauer and Swanson, 2023	0.01	0.84	383	1988M02-2019M12
	Gertler and Karadi, 2015	0.02	0.66	324	1990M01-2016M12
	Romer and Romer, 2004	0.03	0.72	144	1985M01-1996M12
	Smets and Wouters, 2007	0.01	0.93	80	1985Q1-2004Q4
Panel E: Uncertainty shocks					
Uncertainty	Bloom, 2009	-0.03	0.51	396	1985M01-2017M12
	Baker, Bloom, and Davis, 2016	-0.06	0.22	390	1985M07-2017M12
Panel F: Financial shocks					
Financial	Gilchrist and Zakrajšek, 2012	-0.02	0.70	372	1985M01-2015M12
	Bassett et al., 2014	-0.16	0.16	76	1992Q1-2010Q4
Panel G: Fiscal policy shocks					
Fiscal policy	Romer and Romer, 2010	-0.13	0.21	92	1985Q1-2007Q4
	Ramey, 2011	-0.09	0.34	104	1985Q1-2010Q4
	Fisher and Peters, 2010	0.05	0.64	96	1985Q1-2008Q4

Notes: This table shows the correlation of the shipping costs 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 shipping costs surprise series is aggregated by summing across months.

C. Sensitivity and Additional Results

C.1. Sensitivity

Identification strategy. Figure C.1 shows the responses using an instrument that relies on a more restrictive set of events or draft restrictions.

Figure C.2 shows the responses using instruments based on different aggregation methods for the daily surprise series.

Estimation method. Figure C.3 shows the responses estimated based on a local projection on the shock.

Model specification. Figures C.4 and C.5 show the results of sensitivity checks with respect to additional specification choices, including the lag order and deterministics.

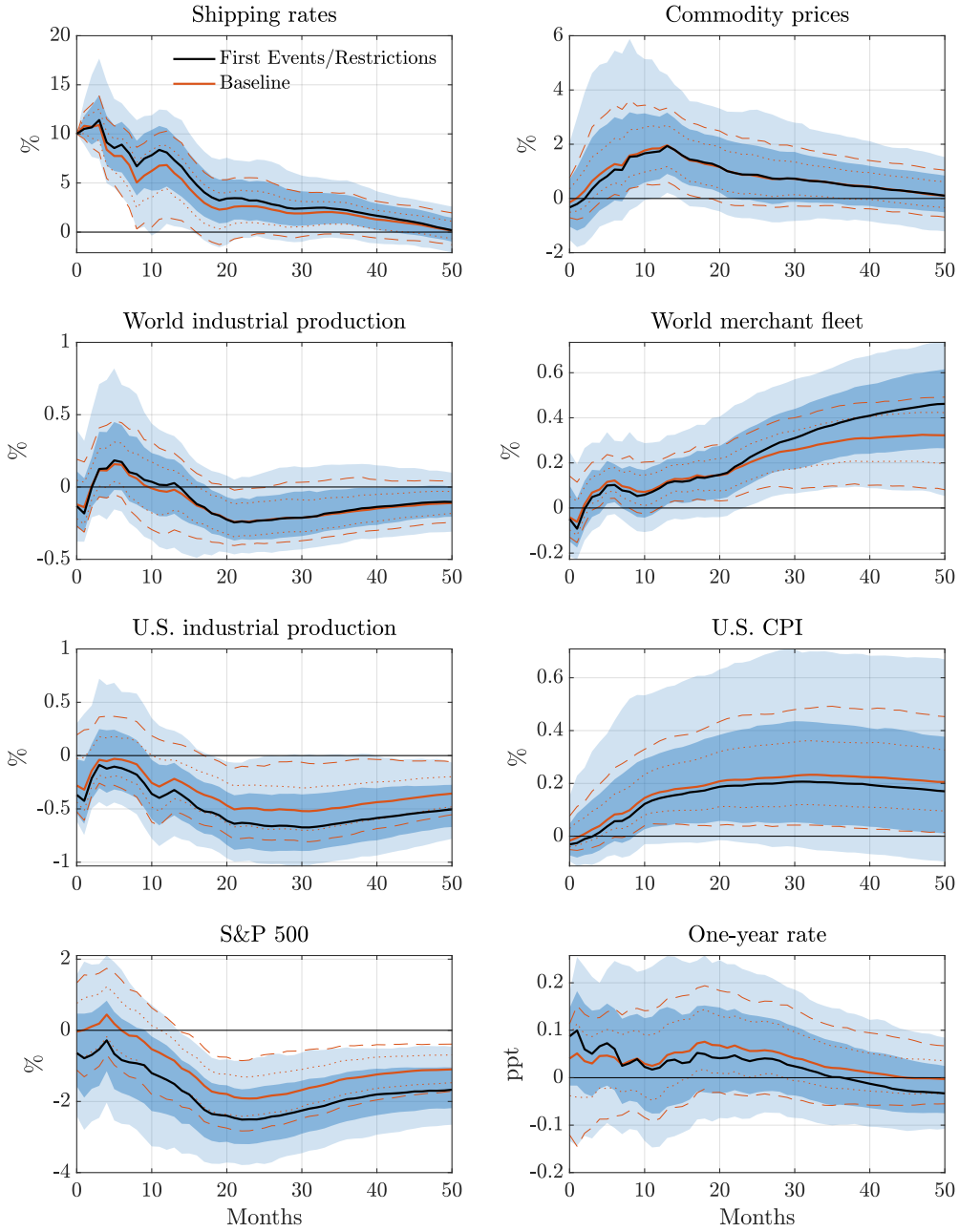
C.2. Additional Results

Shortages. Figure 4a shows the responses of the components of the shortage index constructed by Caldara, Iacoviello, and Yu (2024) to a shipping cost shock.

Uncertainty. Figure 4a shows the responses of various measures of uncertainty to a shipping cost shock.

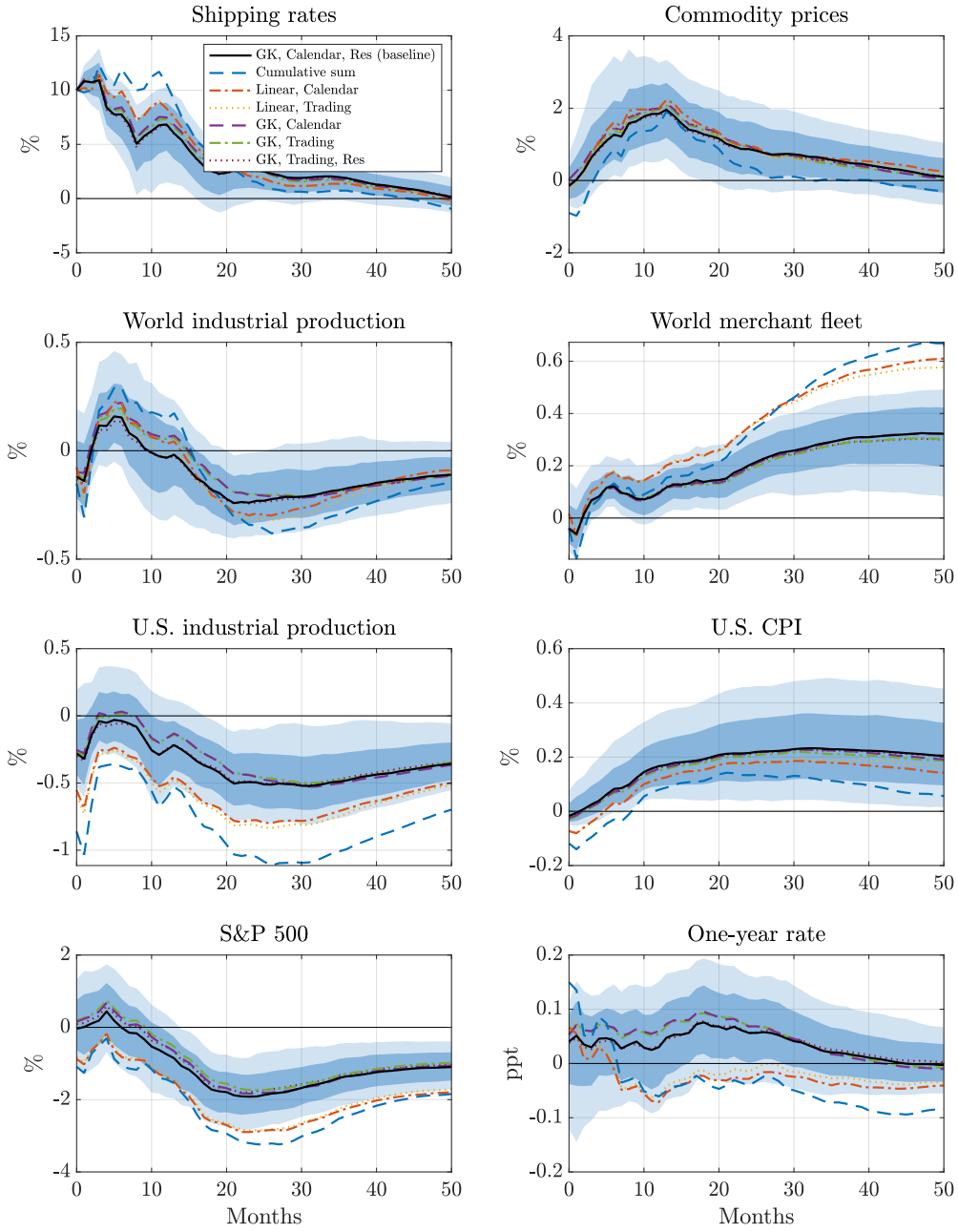
Industrial production. Figure C.8 shows the response of industrial production categories by market group to a shipping cost shock.

Figure C.1: Sensitivity With Respect to Event Selection



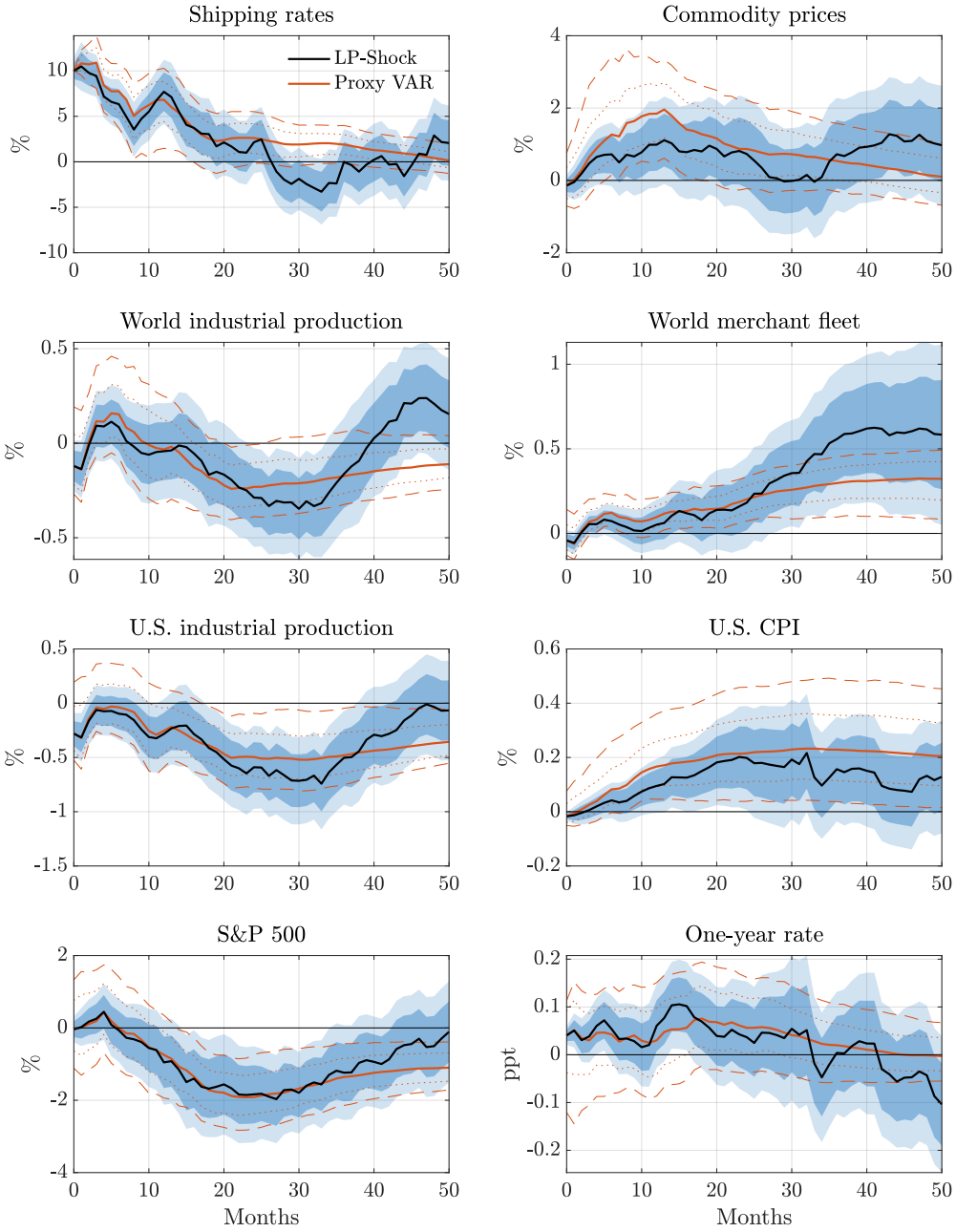
Notes: Impulse responses to a shipping cost shock using an instrument that relies on a more restrictive set of events or draft restrictions. The solid lines are the point estimates and the dark (dotted) and light (dashed) shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.2: Sensitivity With Respect to Aggregation Method for Daily Surprises



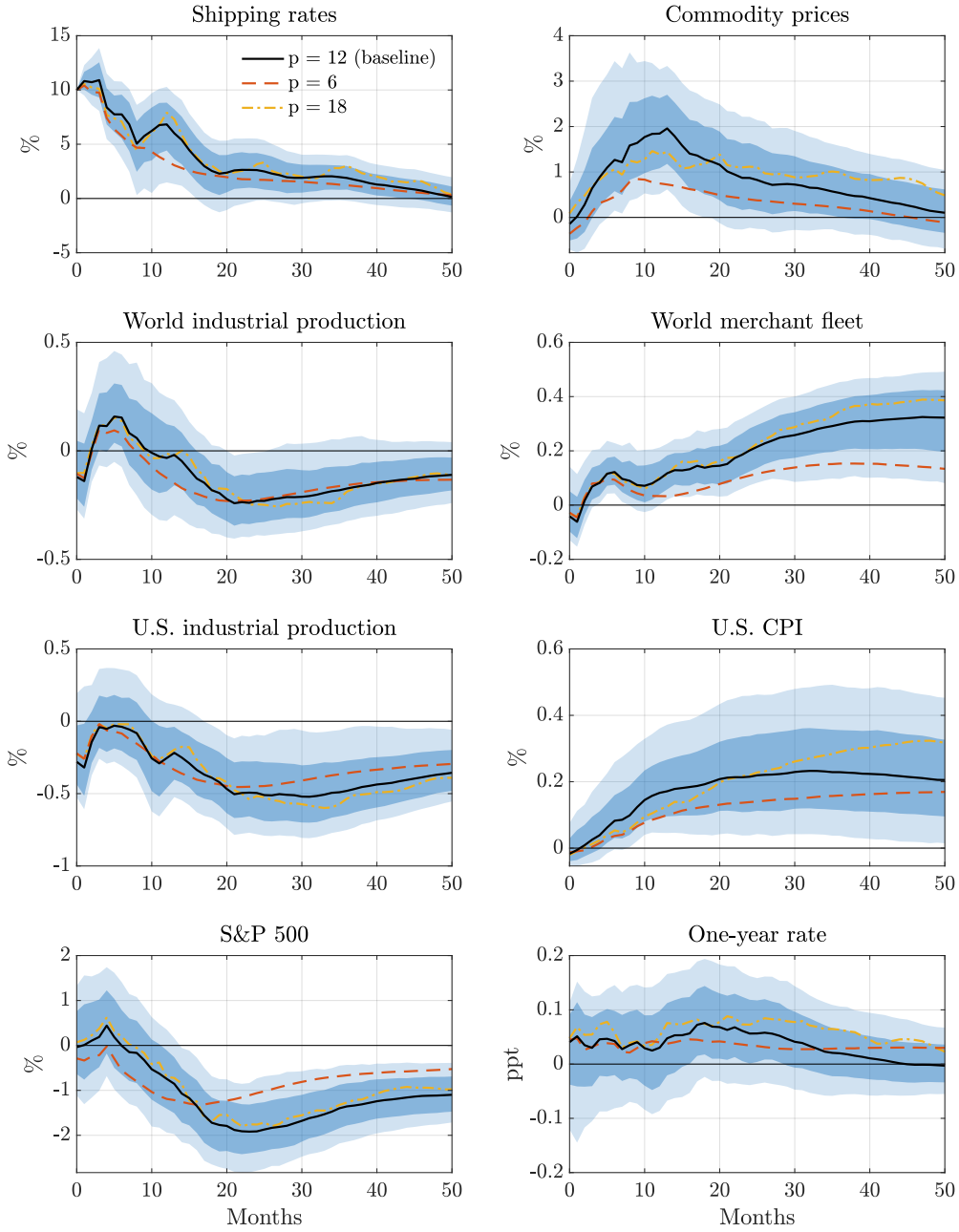
Notes: Impulse responses to a shipping cost shock, using instruments based on different aggregation methods for the daily surprise series. The methods include cumulative sum (equal weights), linear (linear weights), and "GK" (weights proposed by Gertler and Karadi (2015)), with weights for the last two methods based on both the calendar month and trading month. Since the GK method is known to cause serial correlation, we also show results after purging the surprise series of serial correlation by regressing on its lags and using the residual ("res"). The solid lines are the point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.3: Impulse Responses to a Shipping Cost Shock, LP on Shock



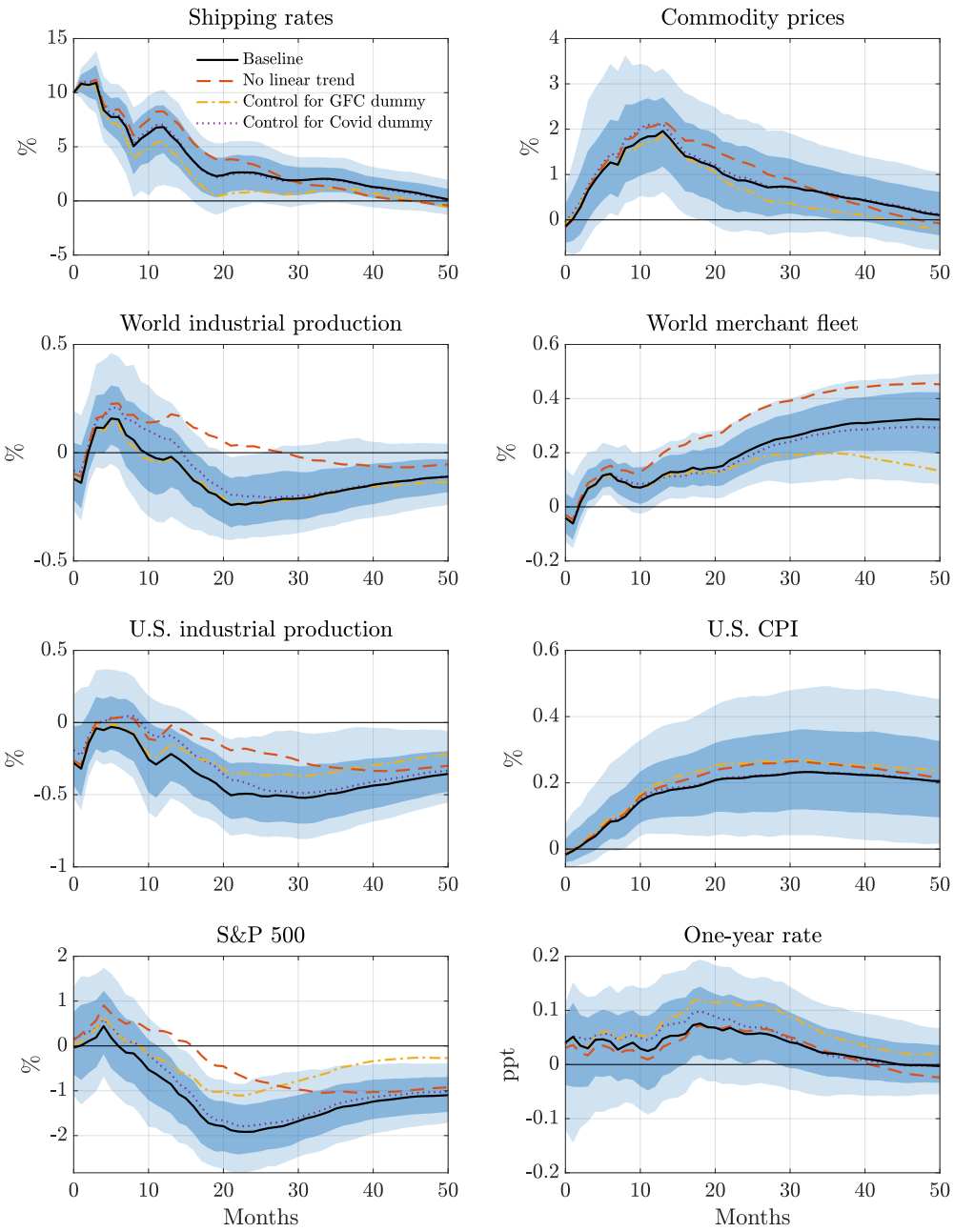
Notes: Impulse responses to a shipping cost shock, normalized to increase real shipping costs by 10 percent, estimated using a local projection (LP) on the shock. The solid lines are the point estimates and the dark (dotted) and light (dashed) shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.4: Sensitivity With Respect to Lag Order



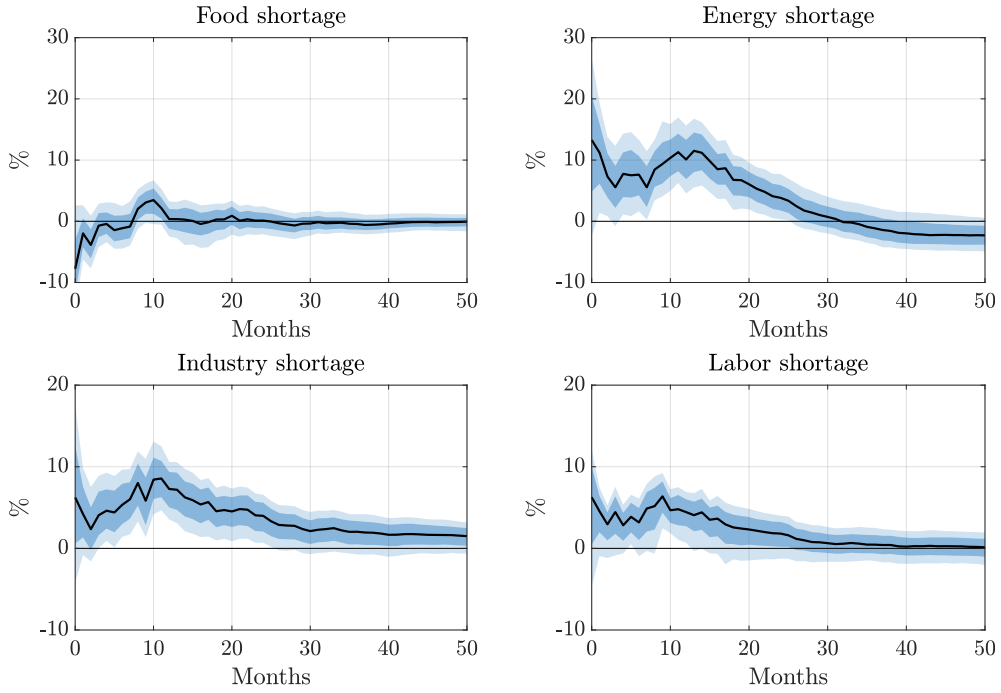
Notes: Impulse responses to a shipping cost shock, estimated using our baseline external instruments VAR, with varying lag order. The lines are the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.5: Sensitivity With Respect to Deterministics



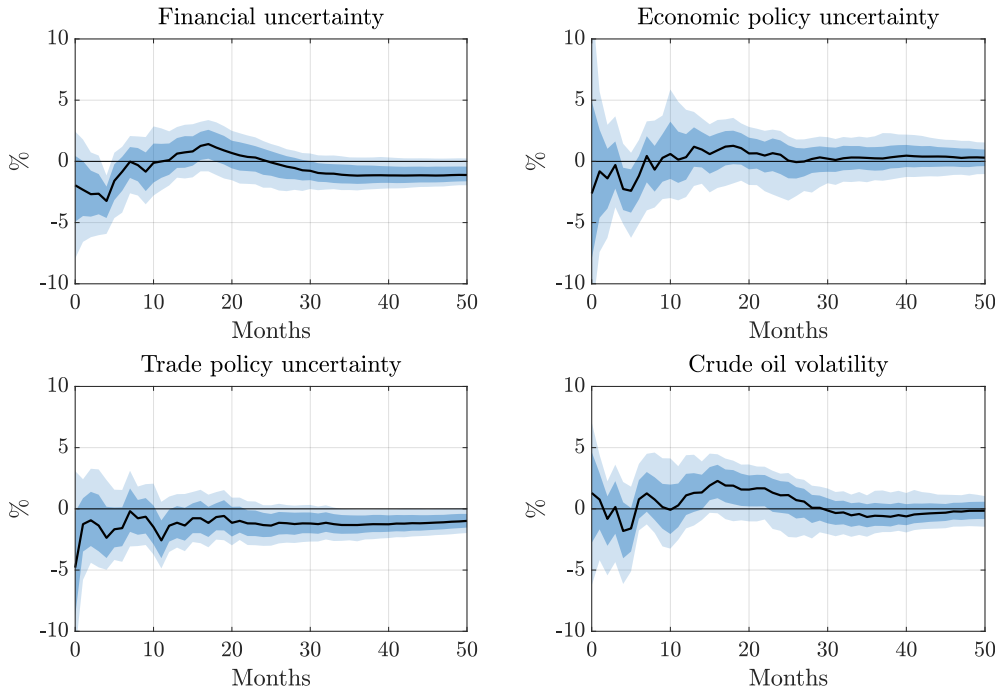
Notes: Impulse responses to a shipping cost shock, estimated using our baseline external instruments VAR, compared to a model that excludes the linear trend, and a model that controls for the global financial crisis (GFC) using a dummy variable. The lines are the point estimate and the dark and light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

Figure C.6: Impacts on Shortage Measures



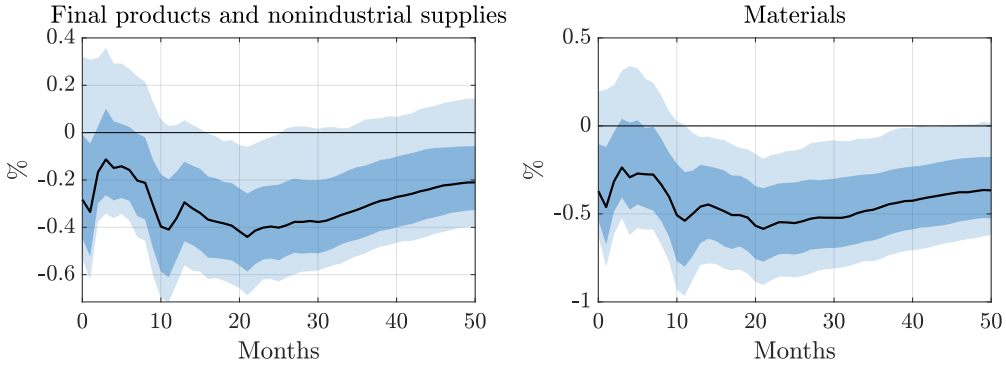
Notes: Impulse responses to a shipping cost shock, normalized to increase real shipping costs by 10 percent on impact. The IRFs are obtained by using our baseline VAR and augmenting it by the variable of interest. The solid line is the point estimate and the dark and light shaded areas are 68 and 90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

Figure C.7: 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 solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure C.8: 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 solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

References Appendix

Baker, Scott R., Nicholas Bloom, and Steven J. Davis (2016). "Measuring economic policy uncertainty". *The Quarterly Journal of Economics* 131.4, pp. 1593–1636.

Barsky, Robert B. and Eric R. Sims (2011). "News shocks and business cycles". *Journal of Monetary Economics* 58.3, pp. 273–289.

Bassett, William F., Mary Beth Chosak, John C. Driscoll, and Egon Zakrajšek (2014). "Changes in bank lending standards and the macroeconomy". *Journal of Monetary Economics* 62, pp. 23–40.

Basu, Susanto, John G. Fernald, and Miles S. Kimball (2006). "Are technology improvements contractionary?" *American Economic Review* 96.5, pp. 1418–1448.

Bauer, Michael D. and Eric T. Swanson (2023). "A reassessment of monetary policy surprises and high-frequency identification". *NBER Macroeconomics Annual* 37.1, pp. 87–155.

Baumeister, Christiane and James D. Hamilton (2019). "Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks". *American Economic Review* 109.5, pp. 1873–1910.

Beaudry, Paul and Franck Portier (2014). "News-driven business cycles: Insights and challenges". *Journal of Economic Literature* 52.4, pp. 993–1074.

Bloom, Nicholas (2009). "The impact of uncertainty shocks". *Econometrica* 77.3, pp. 623–685.

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

Caldara, Dario and Matteo Iacoviello (2022). "Measuring Geopolitical Risk". *American Economic Review* 112.4, pp. 1194–1225.

Caldara, Dario, Matteo Iacoviello, and David Yu (2024). "Measuring Shortages Since 1900". *Working Paper*.

Fisher, Jonas D.M. and Ryan Peters (2010). "Using stock returns to identify government spending shocks". *The Economic Journal* 120.544, pp. 414–436.

Gertler, Mark and Peter Karadi (2015). "Monetary policy surprises, credit costs, and economic activity". *American Economic Journal: Macroeconomics* 7.1, pp. 44–76.

Gilchrist, Simon and Egon Zakrajšek (2012). "Credit spreads and business cycle fluctuations". *American Economic Review* 102.4, pp. 1692–1720.

Hamilton, James D. (2003). "What is an oil shock?" *Journal of Econometrics* 113.2, pp. 363–398.

Hamilton, James D. (2021). "Measuring global economic activity". *Journal of Applied Econometrics* 36.3, pp. 293–303.

Jacks, David S. and Martin Stuermer (2021). "Dry bulk shipping and the evolution of maritime transport costs, 1850–2020". *Australian Economic History Review* 61.2, pp. 204–227.

Känzig, Diego R. (2021). "The macroeconomic effects of oil supply news: Evidence from OPEC announcements". *American Economic Review* 111.4, pp. 1092–1125.

Kilian, Lutz (2008). "Exogenous oil supply shocks: how big are they and how much do they matter for the US economy?" *The Review of Economics and Statistics* 90.2, pp. 216–240.

— (2009). "Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market". *American Economic Review* 99.3, pp. 1053–1069.

Kurmann, André and Christopher Otrok (2013). "News shocks and the slope of the term structure of interest rates". *American Economic Review* 103.6, pp. 2612–2632.

Ramey, Valerie A. (2011). "Identifying government spending shocks: It's all in the timing". *The Quarterly Journal of Economics* 126.1, pp. 1–50.

Romer, Christina D. and David H. Romer (2004). "A new measure of monetary shocks: Derivation and implications". *American Economic Review* 94.4, pp. 1055–1084.

— (2010). "The macroeconomic effects of tax changes: estimates based on a new measure of fiscal shocks". *American Economic Review* 100.3, pp. 763–801.

Smets, Frank and Rafael Wouters (2007). "Shocks and frictions in US business cycles: A Bayesian DSGE approach". *American Economic Review* 97.3, pp. 586–606.