# The Causal Effects of Global Supply Chain Disruptions on Macroeconomic Outcomes: Evidence and Theory*

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**Abstract**

We study the causal effects and policy implications of global supply chain disruptions on the U.S. economy. We construct a new index of supply chain disruptions from the Automatic Identification System data of containerships, developing a novel spatial clustering algorithm that determines real-time congestion from the positions and speeds of containerships in major ports around the globe. We show important differences between our index and the Global Supply Chain Pressure Index that influence the interpretation of supply chain disruptions. We develop a new theoretical framework with search frictions between exporters and importers in the goods market, transportation costs, and spare capacity that provides us with unique identification restrictions for the causal effects of supply chain disruptions. A structural VAR with these restrictions establishes that supply chain disruptions: (i) depress real GDP, raise prices, generate a surge in spare capacity, and (ii) increase the effectiveness of contractionary monetary policy in taming inflation while reducing the sensitivity of output to these policies.

*JEL Classification:* E32, E58, J64.

*Keywords:* supply chain disruptions, search-and-matching in the goods market, SVAR, state-dependence of monetary policy.

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# 1. Introduction

Sudden and large imbalances in the supply and demand for goods, often stemming from disruptions to the supply chain, can lead to protracted deterioration in macroeconomic performance. For instance, the severe disruptions to the flow of goods worldwide during the Covid-19 pandemic led to an unprecedented fall in global trade and a sharp rise in prices, culminating in the second-largest recession in U.S. history.[1] Other prominent examples of potent supply chain disruptions include the blockage of the Suez Canal in 2021 and the war in Ukraine in 2022, both of which resulted in a shortage of goods, increased transportation costs, and a rise in global inflation.[2]

Despite the fundamental role of supply chain disruptions in shaping macroeconomic performance and economic policy, research on this topic is scant and progress is challenged by two key issues. First, existing indices of supply chain disruptions are often inferred from changes in shipping costs or information from surveys on potential disruptions gleaned from the Purchasing Managers' Index (PMI). These measures are problematic since they internalize changes in prices resulting from endogenous movements in the demand for goods, or measurement errors accruing to the subjective perceptions of purchasing managers on supply chain issues, thus providing a potentially biased measurement of supply chain disruptions. The ideal measurement of supply chain disruptions requires data that track the disruptions to the regular flows of goods, which generate the mismatches between supply and demand and the consequent increases in prices. Second, there is no theoretical framework that studies supply chain disruptions considering the spare capacity resulting from the imbalances between the supply and demand for goods. Against this backdrop, mounting evidence points to the adjustment in the spare capacity as a systematic attribute of supply chain disturbances, which is critical to the response of prices and the ensuing policy tradeoffs for the contemporaneous stabilization of prices and output.[3]

1. During the Covid-19 recession (February-April 2020), the decline in GDP from peak to trough was 19.2%. During the Great Depression (August 1929-March 1933), the fall in GDP was 26.7%.

2. See https://www.nytimes.com/2021/03/24/world/middleeast/suez-canal-blocked-ship.html (Accessed July 25, 2023) for coverage on the Suez Canal blockage.

3. Several articles in newspapers and policy institutions discuss the relevance of disruptions to the supply chain for economic performance and macroeconomic policies. See for instance Attinasi et al. (2021), Forster

Our paper addresses these issues by developing: (i) a new index of supply chain disruptions derived from maritime satellite data of containerships, and (ii) a novel theoretical framework that accounts for the spare capacity arising from the imbalances between the supply and demand for goods consequent to the disruption to the supply chain. Using our new data and theory, we shed new lights on the causal effects of global supply chain disruptions and their implications for the effectiveness of monetary policy.

**The measurement of supply chain disruptions**. We study disruptions to the supply chain by examining congestion at container ports. Given the pivotal role of container ports as international hubs for the collection and distribution of tradable goods, even a mild increase in port congestion can significantly impair regular supply chains and generate large imbalances between the supply and demand for goods. More importantly, the itineraries of containerships are rarely altered due to significant switching costs, and the routes of these vessels remain unchanged for the duration of contracts that normally average more than one year, ensuring that congestion at a seaport is minimally influenced by strategic decisions following changes in demand (Wang, Meng, and Jia 2019; Brancaccio, Kalouptsidi, and Papageorgiou 2020; Brancaccio et al. 2023).[4,5] This feature of the shipping segment of containerships enables us to detect supply chain disturbances from the density of inactive vessels stationed at ports.

We quantify port congestion using granular shipping data from the Automatic Identification System (AIS), the mandatory real-time satellite tracking system for containerships across major ports around the globe from 2017 to 2022. By developing a novel machine learning clustering algorithm that utilizes the positions and speeds of containerships recorded in the AIS data, we construct a high-frequency index of Average Congestion Rate (ACR) for major ports worldwide. Our ACR index is the first measurement of global supply chain disruptions derived from maritime satellite data of containerships.[6]

van Aerssen et al. (2021), Grimes and Edgecliffe-Johnson (2021), Dempsey (2022), Lane (2022), and World Bank (2022).

4. Kalouptsidi (2014), Brancaccio, Kalouptsidi, and Papageorgiou (2020), Fuchs and Wong (2022), Wong (2022), and Brancaccio et al. (2023) provide a discussion on the different segments of the maritime shipping industry.

5. In the maritime industry, long-term contracts between exporters and shipowners often have a validity period of one year, with a significant proportion of them lasting even longer due to heightened uncertainty on some specific routes (Bhonsle 2023).

6. The global nature of our ACR index "averages out" any changes in port congestion resulting from

**Theoretical framework**. To interpret the data and study the causal effects of supply chain disruptions, we develop a simple model that accounts for the imbalances in the supply and demand for goods and provides new insights into the effects of these disruptions on the tradeoffs of economic policy. Our model is based on search and matching frictions between exporters and importers in the international product market, building on the disequilibrium model of Barro and Grossman (1971), recast in a microfounded framework by Michaillat and Saez (2015, 2022), and Ghassibe and Zanetti (2022). In our model, exporters supply the goods demanded by importers, and the transactions are mutually costly since they require exporters and importers to pay transportation and visiting costs, respectively. In equilibrium, these costs generate spare capacity and costly congestion. Central to the realization of supply chain disruptions, exporters draw transportation costs from a given distribution in each period, and they decide to ship goods if the drawn cost falls below the threshold for profitable shipments. We assume that a disturbance to the supply chain increases the transportation costs for all exporters, as evinced by the large empirical evidence linking supply chain disturbances and transportation costs (Benigno et al. 2022; Finck and Tillmann 2022; Alessandria et al. 2023; Dunn and Leibovici 2023). We model the general rise in transportation costs as a shift of the distribution of costs to the right of the domain, making it more likely for each exporter to draw transportation costs that exceed the profitability threshold and thus increasing the likelihood of a halt in the shipping of goods. Consequently, the number of unprofitable shipments increases, leading to a fall in the supply of goods available to importers. The model shows that the supply chain shock disrupts economic trade, drives up prices, and widens the spare capacity of exporters.

Our model demonstrates that the responses of macro aggregates to a supply chain disruption shock differ from standard shocks to the demand and supply of goods. Unlike demand shocks, disruptions to the supply chain result in negative co-movements between the quantity and price of goods. While such a property also holds for traditional labor supply shocks, disruptions to the supply chain uniquely increase spare capacity (or equivalently, unemploy-

infrequent adjustments in shipping capacity across routes, thus further underpinning the exogeneity of our ACR index. In addition, since the AIS data offer unparalleled accuracy in tracking real-time movements of tradable goods across the globe, our ACR index is not subject to the same measurement errors as those in the PMI stemming from the subjective perceptions of purchasing managers on supply chain issues.

ment), whereas labor supply shocks decrease it. Therefore, the changes in the spare capacity resulting from the disequilibrium between the supply and demand for goods play a crucial role for the identification of supply chain disruptions.

**The causal effects of supply chain disruptions**. Drawing directly from the prediction of our theoretical model and applying a mix of sign and zero restrictions on the responses of endogenous variables in the Structural Vector Autoregressions (SVARs), we uniquely identify the shocks to the supply chain and distinguish them from traditional labor supply and demand shocks. We estimate the SVAR model using the Bayesian approach, as in Arias, Rubio-Ramirez, and Waggoner (2018), Arias, Caldara, and Rubio-Ramírez (2019), and Arias et al. (2023), and establish several key results. First, a disruption shock to the supply chain leads to a large and immediate drop in real GDP, sharp and persistent increases in both inflation and import prices, and a substantial jump in unemployment. In addition, similar to a labor supply shock, a supply chain disruption shock tends to generate a persistent positive response of inflation, an observation consistent with recent evidence (e.g., Bekaert, Engstrom, and Ermolov (2020) and Gordon and Clark (2023)). Furthermore, the two aggregate supply shocks differ in terms of their effects on unemployment, which is representative of spare capacity. While the initial fall in unemployment in response to the labor supply shock is transitory, the initial increase in unemployment in response to the supply chain disruption shock is persistent, with the median response reverting back to zero at the two-quarter mark.

Second, the decomposition of historical variance shows that the sharp fall in inflation in early 2020 was mainly driven by a significant contraction of aggregate demand that coincided with the first wave of the Covid-19 pandemic across the world. Subsequently, aggregate demand started to rebound, while global supply chain disruptions escalated and made a significant contribution to the rise in inflation. This pattern continued until the end of 2021, with labor supply shocks emerging as the primary driving force for the elevated inflation. In addition, we show that the sharp increase in the Global Supply Chain Pressure Index (GSCPI) – a prominent index to measure supply chain disruptions in both the literature and media – during the first seven months of the pandemic (January-July 2020) was not caused by disruptions to the supply chain. During that time, port congestion was at historical average

levels. Instead, the surge in the GSCPI was likely driven by sudden changes in demand and the management's mis-perception of supply chain issues as recorded by the surveys.[7] We show that the misclassification of disruptions to the supply chain has important implications for the statistical significance of supply chain disruption shocks and the associated policy response, as we discuss below.

**Policy implications**. Our analysis shows that supply chain disruptions generate stagflation and a simultaneous increase in spare capacity. The higher spare capacity constrains the supply of goods and leads to a tighter product market, thus escalating the mismatch between the supply and demand for goods and increasing the sensitivity of prices to movements in demand. As larger shifts in prices are needed to ration the product market, these changes in the relative movements of prices and output increase the effectiveness of monetary policy in stabilizing inflation amid supply chain disruptions. This reinforces findings that show state-dependence in the effectiveness of monetary policy (Benigno and Ricci 2011; Ikeda et al. 2022; Benigno and Eggertsson 2023; Harding, Lindé, and Trabandt 2023).

We test the theoretical prediction by developing a Threshold Vector Autoregression (TVAR) model that estimates the differences in the effects of a contractionary monetary policy shock for different levels of the ACR index. Consistent with our theory, we find that an exogenous tightening of monetary policy leads to a significantly larger and more persistent decline in inflation for a given decrease in output and employment during periods of supply chain disruptions. Our results support a more aggressive, yet less contractionary, monetary policy in response to the elevated inflation consequent to the disturbances to the supply chain. This approach is consistent with the progressive tightening of monetary policy in the U.S. during the supply chain disruptions in the post-Covid-19 recession.

**Related literature**. Our analysis is related to several realms of research. We develop a theoretical framework that maps the mismatch between the supply and demand for goods to changes in prices, real activity, and spare capacity. Our model builds on the disequilibrium framework of Barro and Grossman (1971) by incorporating search and matching frictions in the goods market that result in spare capacity, similar to the studies by Michaillat and Saez

7. Specifically, the GSCPI builds on the PMI, which does not differentiate whether the increase in "delivery times" is caused by a disruption to the supply chain, or to the actual production itself.

(2015, 2022) and Ghassibe and Zanetti (2022). We also link to Brancaccio, Kalouptsidi, and Papageorgiou (2020) and Brancaccio et al. (2023) who develop a search and matching framework to study the role of the transportation sector. Unlike these studies, however, we connect disequilibrium and spare capacity in the goods market with rising transportation costs resulting from the disruptions to the supply chain, and we focus on the impact on prices and real activity and the changes for the tradeoffs of economic policy.

We connect to studies linking the transportation sector to the real economy. Brancaccio, Kalouptsidi, and Papageorgiou (2020) demonstrate the chief role of transportation costs in equalizing comparative advantages across countries and dampening the response of trade flows to shocks. Brancaccio et al. (2023) show that search frictions in the transportation market distort the transportation network and the dynamic allocation of ships over space, requiring pricing rules or taxes to establish efficiency. Dunn and Leibovici (2023) study the drivers of global shipping dynamics, showing that supply chain disruptions lead to an increase in shipping prices and generate aggregate implications. Allen and Arkolakis (2014) link transportation networks to real activity, and Fuchs and Wong (2022) connect them to infrastructure investment. Smirnyagin and Tsyvinski (2022) study the effect of supply chain disasters on asset prices. Li et al. (2022) estimate the patterns of global trade in crude oil, and Bai and Li (2022) investigate the role of congestion in shipping markets for international oil trade and the macroeconomy. In contrast to these studies, we concentrate on the macroeconomic consequences and policy implications of supply chain disruptions arising from the transportation sector.

Finally, we relate to the empirical research that develops SVAR models to study the causal effects of supply chain shocks and differentiate them from alternative shocks to aggregate demand. Representative studies in this large area of research include Balleer et al. (2020), Bekaert, Engstrom, and Ermolov (2020), Brinca, Duarte, and Faria-e-Castro (2021), Shapiro (2022), and Gordon and Clark (2023). Unlike these studies, we base the identification of disturbances to the supply chain on our theory of disequilibrium, and we are the first study to apply in the SVARs an index of global supply chain disruptions that is derived from granular shipping data.

The remainder of our study is organized as follows. Section 2 constructs our ACR index

of supply chain disruptions from satellite data. Section 3 develops our theoretical model and the identification restrictions. Section 4 presents the baseline estimation results and a comparison with the estimation based on the GSCPI. Section 5 explores the state-dependent effects of monetary policy shocks following supply chain disruptions. Section 6 concludes.

# 2. Measuring Global Supply Chain Disruptions

In this section, we develop a novel index designed to track global supply chain disruptions by analyzing imbalances between the supply and demand for goods through the lens of containerized trade. Accounting for 60 percent of the total value of seaborne trade (UNCTAD 2019; OECD and EUIPO 2021), containerized seaborne trade plays an indispensable role in fostering the development and ensuring the smooth operation of global supply chains (Notteboom, Pallis, and Rodrigue 2022).

In the realm of containerized trade, seaports serve as international hubs for freight collection and distribution. Any disruption to these hubs can significantly impair regular supply chains and trade flows. By leveraging the most recent satellite data on the positions and speeds of containerships, available from 2017 onwards, we track port congestion and construct a granular measure of global supply chain disruptions.

## 2.1. AIS Data

We use satellite data from the AIS, the mandatory tracking system required by the International Maritime Organization (IMO) for international voyaging vessels larger than 300 gross tonnage (Heiland et al. 2022). The data provide the comprehensive coverage of the movements of containerships around the globe from January 2017 to July 2022.[8] Each data entry includes the ship's IMO number, timestamp, current draught, speed, heading, and geographical coordinates.[9] The detailed positioning and sailing information enables us to

8. Over 99 percent of international container shipments are carried by containerships that exceed 500 gross tonnage.

9. The draught measures the vertical distance from the bottom of a vessel's keel to the water's surface, indicating how deeply the ship is situated in the water. Although the draught typically reflects a vessel's cargo load (Bai and Li 2022; Li et al. 2022), this measurement can be less informative for containerships since loading and unloading operations often occur simultaneously.

track the behaviors of vessels within various port zones, facilitating the construction of an accurate measure of port congestion.

## 2.2. A Density-Based Spatial Clustering Algorithm

In order to accurately quantify port congestion, we follow the maritime literature by estimating the likelihood that a vessel will first moor in an anchorage area within the port before docking at a berth (Talley and Ng 2016; Karimi-Mamaghan et al. 2020; Bai et al. 2023).[10] Such an estimation requires the precise identification of berth and anchorage areas, a task for which we develop an iterative, multi-attribute, density-based spatial clustering algorithm.

This algorithm identifies the different port areas by focusing on the density of mooring points recorded in the AIS data, which is the instantaneous number of vessels per unit area. It observes that vessels dock at berths in an orderly and close fashion, while mooring in the anchorage areas randomly (Figure 1). The algorithm operates in two layers of clustering. The first layer identifies high-density areas, which are considered potential berth and anchorage areas. The second layer refines these areas by considering additional domain knowledge, such as the heading of ships during mooring and the overlap of ship berthing time.

Our algorithm addresses the challenges faced by existing methods and offers significant advantages over them. The primary challenge is the variability in the density of vessel positions *across* ports with unique geographical morphologies and boundaries. Such a challenge necessitates an adaptive approach to parameter setting for the clustering. Our algorithm is designed to automatically iterate and refine its clustering parameters, thus facilitating the handling of varied and complex port environments. This iterative process not only streamlines the algorithm by reducing the number of inputs but also enhances its generalizability. Another challenge is to accurately distinguish between berth and anchorage areas *within* ports. Our algorithm overcomes this by focusing on the difference in the density of mooring points and incorporating two layers of clustering. This innovative approach based on our domain knowledge significantly increases the granularity and accuracy of our analysis.[11]

10. An anchorage is a location within a port where ships can lower anchors, while a berth is a designated spot within a port where vessels moor to load and unload cargo. If port congestion were not a concern, a ship would dock at a berth immediately upon its arrival in the port to begin loading or unloading cargo.

11. Appendix A and the companion paper Bai et al. (2023) provide details on our clustering algorithm,



**(a)** Headings at a Berth **(b)** Headings at an Anchorage

**Figure 1:** Information on Headings

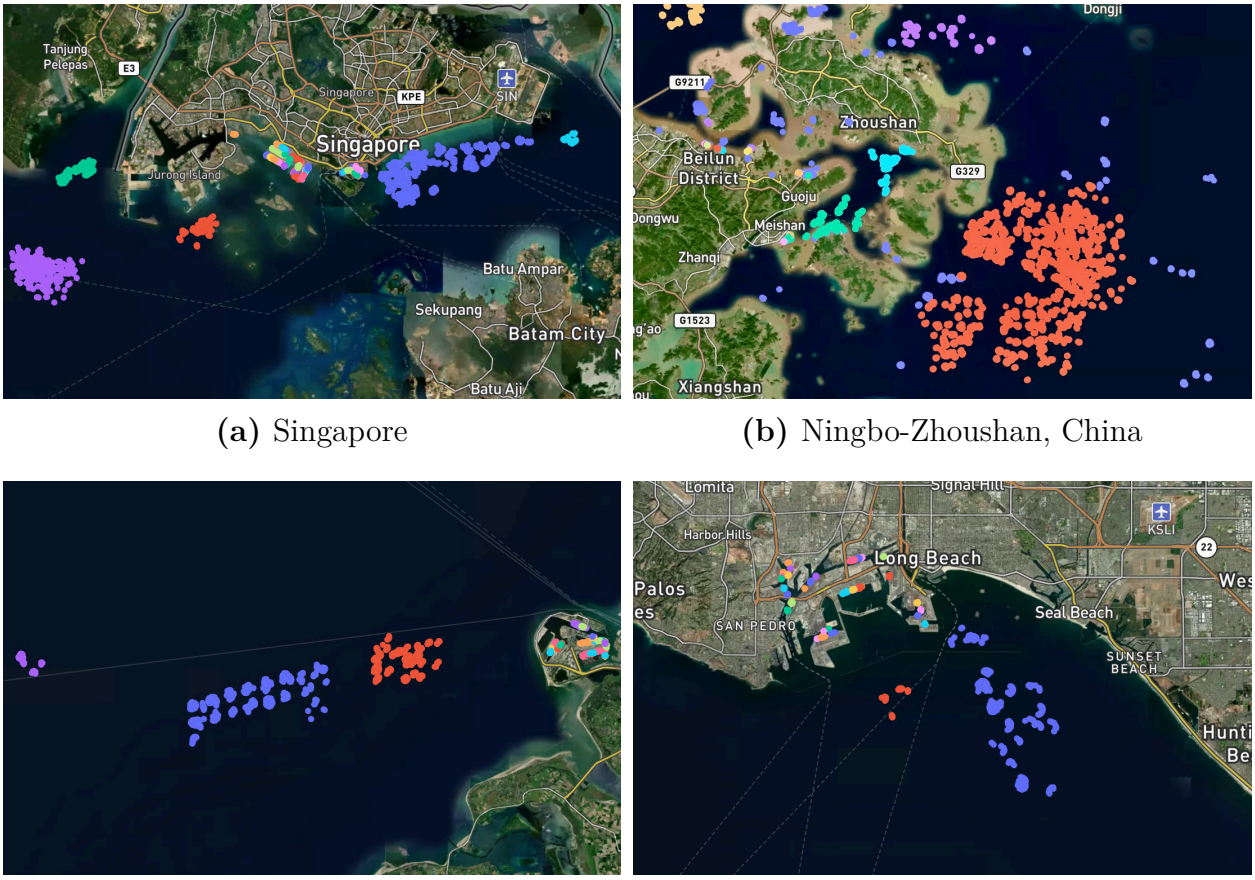
*Notes.* In both figures, a tip represents the bow of a ship. In (a), the headings are either in the same direction or exactly opposite. As a result, two clusters can be formed with exact opposite headings. In (b), the headings are random, with some of them appearing in a ring shape.

To illustrate our algorithm, Figures 2a to 2d show the berth (blue, red, purple, cyan, and orange markers) and anchorage (other colors of markers) areas in the following major container ports: Singapore (Panel a), Ningbo-Zhoushan in China (Panel b), Rotterdam in the Netherlands (Panel c), and Los Angeles and Long Beach in the U.S. (Panel d). Our algorithm accurately captures the berth and anchorage areas in each port, despite the large spectrum of geographical and operational port conditions. By applying our algorithm to the real-time AIS satellite data, we construct a comprehensive, high-frequency measure of global port congestion, as we discuss in the next section.

## 2.3. Port Congestion and the Index of Average Congestion Rate

Port congestion arises when ships cannot immediately load and/or unload cargo upon arrival at ports, resulting in the vessels having to wait in an anchorage area for an opportunity to dock at a berth. We define the Average Congestion Rate (ACR) for a port as the ratio of

including pseudo-codes and a case study involving the Port of Ningbo-Zhoushan in China, which illustrates the effectiveness of our methodology in identifying berth and anchorage areas in ports with different morphologies compared to alternative methods.




**(a)** Singapore **(b)** Ningbo-Zhoushan, China

**(c)** Rotterdam, Netherlands **(d)** Los Angeles and Long Beach, U.S.

**Figure 2:** Identification of Anchorage and Berth Areas of a Port Using Machine Learning

*Notes.* The figures plot the identification results of the berth and anchorage areas for each of the following representative container ports worldwide: the Port of Singapore, Port of Ningbo-Zhoushan in China, Port of Rotterdam in the Netherlands, and the Ports of Los Angeles and Long Beach in the U.S. We use different colors to depict various clusters identified by our machine learning clustering algorithm (IMA-DBSCAN; see Appendix A for details); specifically, we use blue, red, purple, cyan, and orange to represent clusters identified as anchorages, and the other colors to represent clusters identified as berths. The underlying sample for each figure takes the first 50,000 AIS observations of containerships entering each port since 1 January 2020.

containerships that moor at an anchorage before docking at a berth to the total number of port calls.[12] We calculate the monthly ACR for the top 50 container ports worldwide during the sample period.

We derive a time series measure of global supply chain disruptions by computing the weighted average of the ACR series for the top 50 container ports worldwide, with the

12. A port call refers to the arrival of a ship at a specific port where it docks to load or unload cargo.

weights determined by the number of port calls and thus reflecting the distinctive roles of different ports within the global supply chain.[13] Figure 3 displays our ACR index. Prior to 2019, the index remained stable around the sample median (18.1%), and it declined to 16% from early 2019 to mid-2020. Subsequently, the index consistently rose to reach its peak at 27% in June 2021, indicative of the significant disruptions to the supply chain caused by the Covid-19 pandemic.

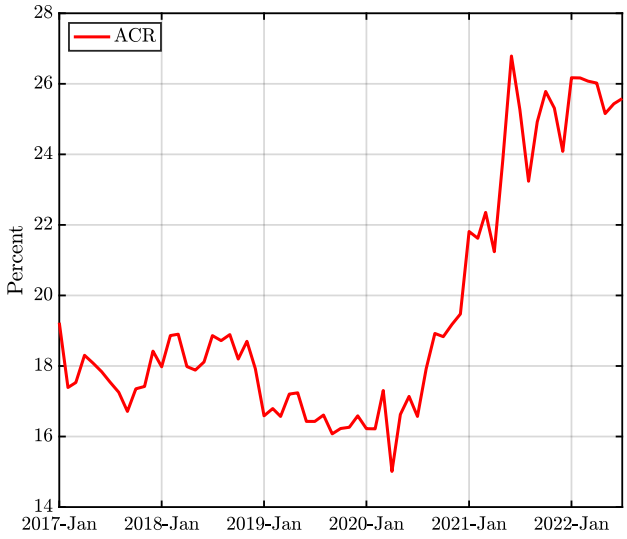



**Figure 3:** ACR Index of Global Supply Chain Disruptions

*Notes.* The ACR index of global supply chain disruptions is derived by taking a weighted average of the ACR series for the top 50 global container ports. The number of port calls serves as the weight for each port. The index is presented in percentage terms and has been seasonally adjusted. For the complete ranking of container ports, please refer to https://www.worldshipping.org/top-50-ports (Accessed June 15, 2022).

Figure 4 presents the monthly ACR series for the top ten container ports worldwide that are located in China, Singapore, South Korea, and the Netherlands, as well as the Ports of Los Angeles and Long Beach in the U.S., for the period from January 2017 to July 2022 when the AIS data are available. Following the onset of the Covid-19 pandemic in March 2020, the ACR indices for several ports remained largely stable (e.g., Port of Rotterdam, Netherlands), while only a few decreased (e.g., Port of Shanghai, China). However, as the pandemic progressed from October 2020 onwards, congestion increased in the majority of

13. The weighting considers the differential impact on global supply chain disruptions resulting from changes in the ACR at different ports. For instance, a slight increase in the ACR at the Port of Hong Kong in China would likely have triggered a more pronounced global supply chain disruption than a significant increase at the Port of Manila in the Philippines.

ports, as evinced by the increase in chromatic intensity in the figure.[14] This implies that containerships encountered significant delays in the loading and/or unloading operations since October 2020, thus disrupting the international freight collection and distribution of tradable goods.

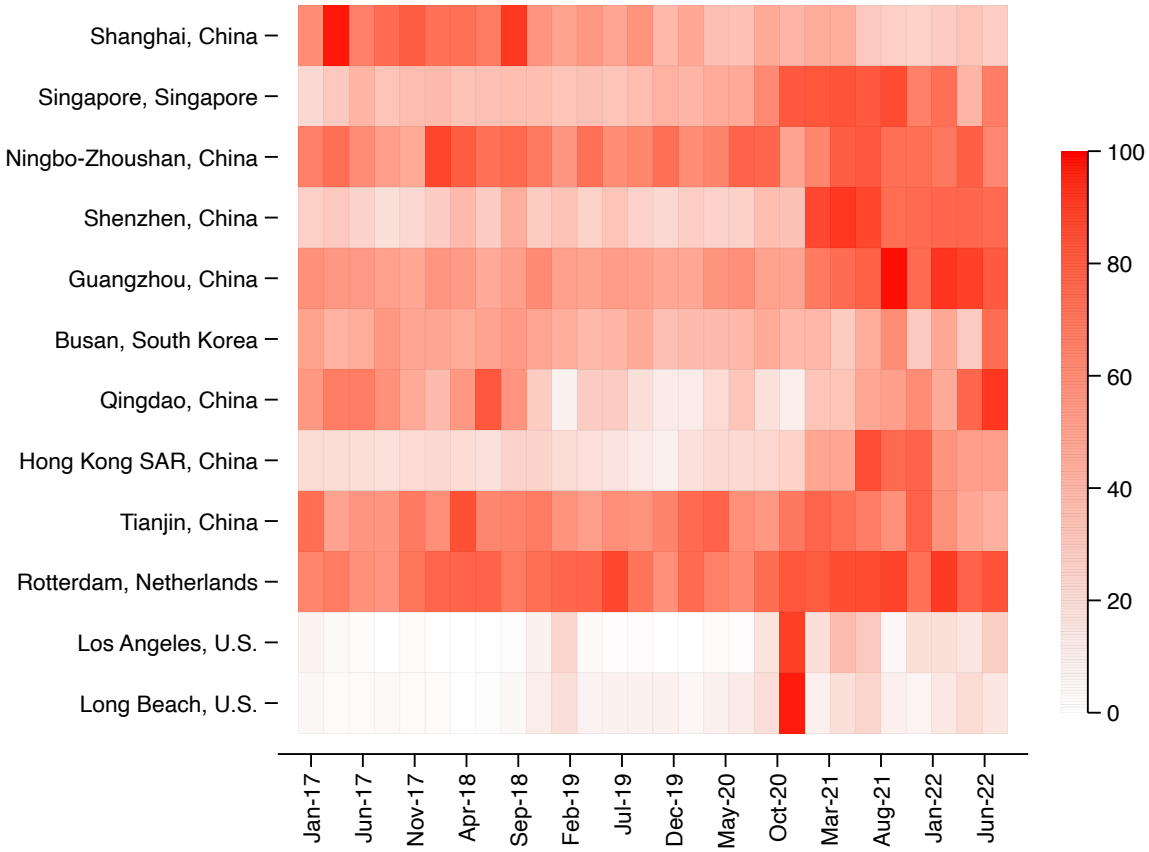
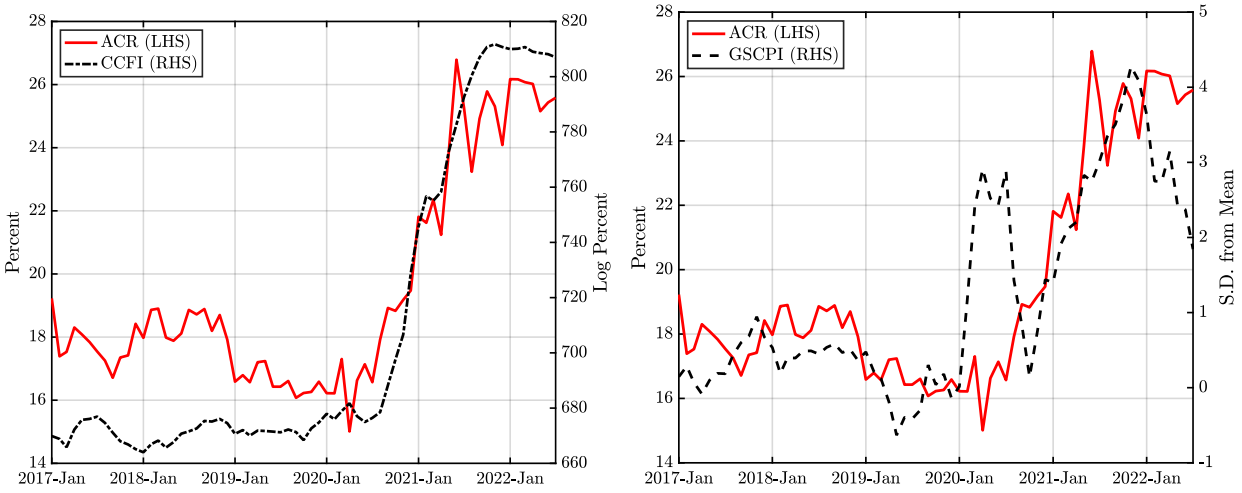



**Figure 4:** ACR for the Major Container Ports Worldwide

*Notes.* The heatmap presents the monthly ACR series for the top ten global container ports and the Ports of Los Angeles and Long Beach in the U.S., covering the period from January 2017 to July 2022. The ACR series for each port is normalized, expressed as a percentage of its peak value observed within the sample period. Cells in a darker shade indicate greater congestion for the corresponding port during the designated month. The ACR of a port is defined as the proportion of containerships that moor at an anchorage area before docking at a berth, relative to the total number of port calls.

14. By our calculation, in late-2020, over 80% of inbound ships at the Port of Los Angeles in the U.S. were unable to dock at a berth immediately upon arrival. This observation aligns with official statistics. For instance, according to figures released by the Pacific Merchant Shipping Association, the percentage of containerships at Los Angeles waiting five or more days for unloading surged from 10% in August to 26% in December 2020. Additionally, the Marine Exchange of Southern California reported that the number of vessels anchored in Los Angeles waters also rose from fewer than 20 in August to more than 35 in December 2020.

Furthermore, we plot in Figure 5a the ACR index against the China Containerized Freight Index (CCFI), which is a widely-accepted measure of cross-border transportation costs. We find that they moved together since the onset of the pandemic. As the delay in container processing became prevalent, port congestion escalated and ships were tied up in ports, leading to a massive shortage in the supply of shipping services and hence a skyrocketing shipping price. Nevertheless, it is also noteworthy that the two series did not track closely with each other before the pandemic. This is intuitive because the shipping price is an equilibrium object and the changes in it are subject to both demand- and supply-side factors.




**(a)** ACR vs. CCFI **(b)** ACR vs. GSCPI

**Figure 5:** Comparison Between the ACR and Other Measures of Supply Chain Disruptions

*Notes.* Figure 5a plots the ACR (red solid line) against the CCFI (black dotted line), while Figure 5b plots the ACR against the GSCPI (black dashed line) during the sample period from January 2017 to July 2022. The ACR is computed using the AIS data of containerships and the IMA-DBSCAN algorithm developed in Appendix A. The CCFI is computed using the monthly average of the original CCFI composite index (Source: https://en.sse.net.cn/ (Accessed May 12, 2022)). The GSCPI is retrieved from the New York Fed's website (Source: https://www.newyorkfed.org/research/policy/gscpi#/overview (Accessed August 10, 2022)). The ACR is measured as a percentage, the CCFI is measured in log percent, and the GSCPI is measured in standard deviations from the mean. All the series are seasonally adjusted.

Lastly, we compare our ACR index with the GSCPI to highlight the differences in the measurement of supply chain disruptions. The GSCPI uses information on cross-border transportation costs and sub-components of the country-specific manufacturing PMI to infer supply chain disruptions. As discussed in the introduction, such measurement is problematic since the transportation costs may reflect endogenous changes in prices due to adjustments in

the demand for goods, and the information gathered from purchasing managers may reflect subjective views rather than actual disturbances to the supply chain.[15] In contrast, our ACR index uses maritime satellite data to estimate the congestion at seaports around the globe. It is a pure supply-side measure, as changes in demand rarely alter the fixed itineraries on which the containerships operate, hence exerting little influence on port congestion (Brancaccio, Kalouptsidi, and Papageorgiou 2020; Brancaccio et al. 2023).[16] Furthermore, any infrequent adjustments in shipping capacity across routes, and the resulting changes in congestion at different ports, would be canceled out when we aggregate the indices of port congestion to construct the ACR index.

Figure 5b displays the ACR and GSCPI indices over the sample period from January 2017 to July 2022. Before 2020, the dynamics of the two indices were similar, but the GSCPI substantially increased at the onset of the Covid-19 pandemic in early 2020 and remained elevated in the first half of the year. From the second half of 2020 onwards, the two series increased similarly until January 2022. di Giovanni et al. (2022) attributes the jump in the GSCPI in early 2020 to the onset of the Chinese lockdown, and the sudden fall in the second half of 2020 to the partial reopening of China and Europe. Our index of congestion in ports indicates that the initial lockdown in China was not accompanied by high congestion in ports of the size needed to generate a global supply chain disruption, and, equally, the reopening of China and Europe did not substantially influence the congestion in ports. Thus, the changes in the GSCPI are likely driven by sudden changes in demand and the management's misperception of supply chain issues as recorded by the PMI surveys. It is also observed that the two series diverged from each other again in early 2022, as the ACR remained elevated while the GSCPI had already started plummeting. We argue that the high ACR could be largely attributed to the stringent containment measures that were still in place in China during the first half of 2022, continuously exerting pressure on the global supply chain.

15. Appendix B elaborates on the shortcomings of using the shipping cost, sub-components of the manufacturing PMI, and other indices of supply chain disruptions in the causality assessment.

16. This is because diversions in shipping routes usually incur a large transition cost. They also severely affect the stability of shipping operations and the loyalty of customers (Wang, Meng, and Jia 2019). Therefore, the effects of demand shifters on our ACR index are limited. In Appendix F.3, we confirm this point through a robustness check of our baseline results; by applying a fitted ACR in our estimation after regressing the port-specific ACR on the Oxford Stringency (OS) index (Mathieu et al. 2020) and port fixed effects, we find that our main results still hold.

# 3. A Model of Congestion and Spare Capacity

In this section, we develop a model featuring imbalances in the supply and demand for goods that result in spare capacity. The model is based on search and matching frictions in the international product market similar to the framework in Michaillat and Saez (2015, 2022) and Ghassibe and Zanetti (2022), and incorporates transportation costs that generate the separation of unprofitable matches.[17] Our model illustrates the central role of spare capacity in uniquely identifying supply chain disruptions (Section 4) and links these disruptions to the efficacy of monetary policy in controlling inflation (Section 5).

The economy is composed of maximizing firms and households. Firms can be either exporters or importers. Exporters produce goods using a fixed amount of labor supplied by households and incur transportation costs to sell the goods. Importers buy these goods from exporters and sell them to the households.[18] Households purchase goods from importers using money that is the numeraire in the economy.

In the rest of this section, we begin by studying the separate problems of exporting and importing firms that face transportation and visiting costs, respectively, to derive the aggregate supply. We then study the problem of households, who determine the aggregate demand. Consequently, we show that in equilibrium, search frictions and transportation costs determine the spare capacity in the economy that is critical to the study of disruptions to the supply chain.

## 3.1. Firms

Firms comprise exporters and importers. Exporters produce goods with a capacity determined by labor inputs $l > 0$ that are inelastically supplied by households. Exporters supply goods to the importers in a frictional goods market that prevents the sale of full capacity. Each unmatched (identified by the subscript $U$) importer makes visits $i_U$ to unmatched ex-

17. Appendix C provides a discussion on the evidence of matching frictions in the international product market and the separation of commercial trade linked to transportation costs.

18. Our approach is similar to the standard assumption that firms require internationally imported intermediate goods for the production of final goods. See, for instance, Costinot, Vogel, and Wang (2013), Kasahara and Lapham (2013), and Ramondo and Rodríguez-Clare (2013) and the references therein.

porters at a unitary cost $\rho > 0$ and sells the purchased goods to households at the set price $p$ if the purchasing visit is successful. Matching frictions prevent the successful matching of all visits.

*Matching process.* In each period, a constant-returns-to-scale matching function encapsulates search frictions in the product market, determining the number of meetings ($\mathscr{m}$) between unmatched exporters and importers according to:

$$\mathscr{m} = (x_U^{-\xi} + i_U^{-\xi})^{-\frac{1}{\xi}}, \tag{1}$$

where $x_U$ and $i_U$ are the number of unmatched exporters and importers, respectively, and the parameter $\xi$ is the elasticity of substitution between the inputs of the matching function. We assume $\xi > 0$, such that $\mathscr{m} \leq \min\{x_U, i_U\}$.

We define the product market tightness $\theta$ as the ratio between the number of visits by the unmatched importers and the number of unmatched exporters, such that $\theta \equiv i_U/x_U$. Given the law of large numbers, product market tightness is taken as given by single exporters and importers, and it determines the probabilities that exporters and importers meet each others given the constant returns to scale in the matching function. Specifically, the probability for an exporter to meet an importer is:

$$f(\theta) = \frac{\mathscr{m}}{x_U} = (1 + \theta^{-\xi})^{-\frac{1}{\xi}}, \tag{2}$$

and the probability for an importer to meet an exporter with probability:

$$q(\theta) = \frac{\mathscr{m}}{i_U} = (1 + \theta^{\xi})^{-\frac{1}{\xi}}. \tag{3}$$

The function $f(\theta)$ is smooth and strictly increasing in the domain $[0, +\infty)$, with $f(0) = 0$, $\lim_{\theta\to+\infty} f(\theta) = 1$, and $f'(\theta) > 0$, whereas the function $q(\theta)$ is smooth and strictly decreasing in the same domain $[0, +\infty)$, with $q(0) = 1$, $\lim_{\theta\to+\infty} q(\theta) = 0$, and $q'(\theta) < 0$. Two properties that will be useful later are that $f(\theta)/q(\theta) = \theta$ and $df(\theta)/d\theta = q(\theta)^{1+\xi}$.

*Transportation cost.* Exporters pay an idiosyncratic transportation cost to export goods.[19]

19. Our main results still hold when we assume that the transportation cost is borne by importers instead. This is because the match separation condition (12) is invariant to such a modeling choice.

Specifically, in each period, exporters draw a transportation cost $z$ from the log-normal distribution $G(z)$ with parameters $\gamma$ and $\sigma$, i.e., $G(z) \equiv \Phi\big[(\log z - \gamma)/\sigma\big]$, where $\Phi(\cdot)$ is the standard normal cumulative density function.[20] As we discuss later, there exists a reservation level of transportation cost $\bar{z}$, above which matches are unprofitable and therefore severed. Consequently, the matches with a draw of transportation cost higher than the reservation level ($z > \bar{z}$) are severed, whereas they continue otherwise ($z \leq \bar{z}$).

*Recursive value functions*. At the beginning of each period, the matched exporters sell the produced goods to importers and pay the transportation costs, and the matched importers sell their imported goods to households and pay the import prices. The exporters and importers that are unmatched search to form a match with each other. At the beginning of the next period, all the exporters draw new transportation costs and the profitable matches continue while the unprofitable matches are severed (we describe the match separation decision later in the section).

Four recursive value functions describe the values for the different status of exporters and importers. The value for a matched (identified by the subscript $M$) exporter, $X_M(z)$, is equal to:

$$X_M(z) = r(z) - z + \beta \mathbb{E}_{z'}\big[\max\big(X_M(z'), X_U\big)\big], \tag{4}$$

where $r(z)$ is the import price that is endogenously determined, $z$ is the cost of transportation, $\beta$ for the discount factor, and $z'$ for the draw of transportation cost at the beginning of the next period. Equation (4) shows that the present value of being a matched exporter is the profit margin $r(z) - z$, plus the continuation value which depends on whether the exporter endogenously separates from the match. Such a decision is determined by $z'$, and hence the max operator characterizes the optimal continuation/separation decision.

The value for an unmatched exporter, $X_U$, is:

$$X_U = \beta f(\theta) \mathbb{E}_{z'}\big[\max\big(X_M(z'), X_U\big)\big] + \beta\big(1 - f(\theta)\big) X_U. \tag{5}$$

20. We could also apply a more general setup that each exporter maintains its previous draw of transportation cost with probability $1 - \varphi$, and with probability $\varphi$, the exporter draws a new transportation cost from $G(z)$. This setup is often found in the traditional labor search and matching theory that studies the labor market outcomes following a rise in economic turbulence (den Haan, Ramey, and Haefke 2005; Fujita 2018). Despite more tedious algebra, our main results still hold.

With probability $f(\theta)$, the unmatched exporter meets an importer and then decides whether to endogenously separate if the given draw of transportation cost makes the match unprofitable. With probability $1 - f(\theta)$, the exporter does not meet an importer and hence continues being unmatched.

On the other side of the market, the value of matched importer, $I_M(z)$, is:

$$I_M(z) = p - r(z) + \beta \mathbb{E}_{z'} \big[ \max \big( I_M(z'), I_U \big) \big]. \tag{6}$$

The importer earns $p$ by selling the imported goods to the households and it pays the import price $r(z)$ to the exporter. The max operator characterizes the optimal continuation/separation decision conditional on the draw of transportation cost at the beginning of the next period. If the drawn transportation cost makes the match unprofitable, the importer endogenously separates from the match and hence starts the next period with a value equal to:

$$I_U = -\rho + \beta q(\theta) \mathbb{E}_{z'} \big[ \max \big( I_M(z'), I_U \big) \big] + \beta \big( 1 - q(\theta) \big) I_U, \tag{7}$$

where $\rho$ is a fixed cost to pay per visit. We assume free entry into the international product market that drives the value for an unmatched importer to zero in equilibrium, i.e., $I_U = 0$.

*Nash bargaining*. Nash bargaining splits the total surplus from the matching between the exporter and the importer. The total surplus from matching is equal to:

$$S(z) = X_M(z) - X_U + I_M(z) - I_U. \tag{8}$$

According to Nash bargaining, the exporter earns a constant share $\eta$ of the total surplus, and the importer earns the remaining share $1 - \eta$, which in equilibrium yields:

$$\eta \big( I_M(z) - I_U \big) = (1 - \eta) \big( X_M(z) - X_U \big). \tag{9}$$

Given the equilibrium rule (9), the value functions (4), (5), (6), and the free entry condition $I_U = 0$, the import price that splits the surplus according to Nash bargaining is equal to:

$$r(z) = \eta(p + \rho\theta) + (1 - \eta)z. \tag{10}$$

Equation (10) shows that the bargaining power $\eta$ is central to the determination of the

import price. When the exporters have significant bargaining power ($\eta \to 1$), they earn the total surplus accrued to the importers from selling the goods to the household ($p + \rho\theta$). On the other hand, when the bargaining power of the exporter is low ($\eta \to 0$), the import price is close to the cost of transportation ($z$). Intermediate values for the bargaining parameter proportionally split the total surplus between exporters and importers, with the share of surplus determined by the bargaining parameter. Importantly for our analysis, congestion in the matching process, captured by tightness in the product market, worsens the bargaining position of importers by lowering their matching probability, thus increasing the price they are willing to pay to buy goods from exporters.

*Match separation*. Since the total value for a matched exporter and a matched importer, i.e., $X_M(z) + I_M(z)$, strictly decreases with the cost of transportation $z$, there exists a cut-off transportation cost $\bar{z}$, above which the matches become unprofitable and are severed. This cut-off makes the total surplus in Equation (8) equal to zero, as follows:

$$S(\bar{z}) = 0. \tag{11}$$

By substituting the value functions (4), (5), (6), and the free entry condition $I_U = 0$ into Equation (11), we can express the match separation condition as a function of price $p$, reservation transportation cost $\bar{z}$, and product market tightness $\theta$, defined for all $p \in (0, +\infty)$, $\bar{z} \in (0, +\infty)$, and $\theta \in [0, +\infty)$, satisfying:

$$\mathbb{F}(p, \bar{z}, \theta) = p - \bar{z} + \big(1 - \eta f(\theta)\big)\beta \mathbb{E}_{z'} S(z') = 0, \tag{12}$$

where the expected surplus is defined by $\mathbb{E}_{z'} S(z') = \int_0^{\bar{z}} S(z') dG(z')$.

*Match creation*. Using the value function for an unmatched importer (7) and the free entry condition $I_U = 0$, we define the match creation condition as a function of reservation transportation cost $\bar{z}$ and product market tightness $\theta$, defined for all $\bar{z} \in (0, +\infty)$ and $\theta \in [0, +\infty)$, satisfying:

$$\mathbb{H}(\bar{z}, \theta) = \frac{\rho}{\beta q(\theta)} - (1 - \eta)\mathbb{E}_{z'} S(z') = 0, \tag{13}$$

where $\mathbb{E}_{z'} S(z') = \int_0^{\bar{z}} S(z') dG(z')$.

*Aggregate supply*. The aggregate supply in the economy results from the steady-state equilibrium in the international product market, which is defined as:

**Definition 1.** *The steady-state equilibrium in the international product market consists of a price* $p \in (0, +\infty)$*, a reservation transportation cost* $\bar{z} \in (0, +\infty)$*, and a product market tightness* $\theta \in [0, +\infty)$ *such that the conditions for match separation* (12) *and match creation* (13) *simultaneously hold:*

$$\mathbb{F}(\bar{z}, \theta, p) = \mathbb{H}(\bar{z}, \theta) = 0.$$

Definition 1 indicates that the equilibrium product market tightness is a function of price and reservation transportation cost. This relationship is determined by the conditions of match separation and creation, as stated in Equations (12) and (13), respectively.

**Proposition 1.** *In equilibrium, the price* $p$*, reservation transportation cost* $\bar{z}$*, and product market tightness* $\theta$ *satisfy the relationship:*

$$\theta(p, \bar{z}) = \frac{1-\eta}{\eta\rho}\big(p - \bar{z} + \beta \int_0^{\bar{z}} G(z')dz'\big), \tag{14}$$

*where* $G(.)$ *is the log-normal cumulative density function. Hence, the product market tightness* $\theta$ *has the following properties:*

1. $\theta(p^{min}, \bar{z}) = 0$ *and* $\lim_{p\to+\infty} \theta(p, \bar{z}) = +\infty$*, where* $p^{min}$ *satisfies:*

$$p^{min} - \bar{z} + \beta \int_0^{\bar{z}} G(z')dz' = 0;$$

2. $\theta(p, \bar{z})$ *is strictly increasing on* $[p^{min}, +\infty)$*;*

3. $\theta(p, \bar{z})$ *is linear on* $[p^{min}, +\infty)$*;*

4. $\lim_{\bar{z}\to 0^+} \theta(p, \bar{z}) = (1-\eta)p/(\eta\rho)$ *and* $\theta(p, \bar{z}^{max}) = 0$*, where* $\bar{z}^{max}$ *satisfies:*

$$p - \bar{z}^{max} + \beta \int_0^{\bar{z}^{max}} G(z')dz' = 0;$$

5. $\theta(p, \bar{z})$ *is strictly decreasing on* $(0, \bar{z}^{max}]$*; and*

6. $\theta(p, \bar{z})$ *is convex on* $(0, \bar{z}^{max}]$.

*Proof.* See Appendix D.1. ■

Proposition 1 establishes that the product market tightness strictly increases with the price of goods and decreases with the reservation transportation cost. These properties are intuitive. When the total surplus rises due to a higher price, importers visit more exporters. Conversely, a higher reservation transportation cost reduces the total surplus shared between exporters and importers at the margin. This, in turn, dampens the incentives for importers to visit exporters, leading to a slack product market.[21]

Next, the aggregate supply comprises the quantity of goods traded by the importers and exporters that survive separation for a given productive capacity $l$. To determine the steady-state number of matched exporters, we consider the law of motion for the number of matched exporters at the beginning of the next period:

$$x'_M = G(\bar{z})x_M + f(\theta)G(\bar{z})x_U,$$

and that for the number of unmatched exporters at the beginning of the next period:

$$x'_U = \big[1 - f(\theta) + f(\theta)\big(1 - G(\bar{z})\big)\big]x_U + \big(1 - G(\bar{z})\big)x_M.$$

By focusing on the steady-state equilibrium and normalizing the total number of matched and unmatched exporters to one, i.e., $x_M + x_U = 1$, we derive the equilibrium number of matched exporters $x_M^{eqm}$ equal to:

$$x_M^{eqm}(\bar{z}, \theta) = \frac{f(\theta)G(\bar{z})}{1 - G(\bar{z}) + f(\theta)G(\bar{z})}.$$

Hence, the aggregate supply in the economy is equal to the quantity of goods supplied by matched exporters for a given productive capacity $l$:

$$c_s(\bar{z}, \theta) = x_M^{eqm}(\bar{z}, \theta) \cdot l = \frac{f(\theta)G(\bar{z})}{1 - G(\bar{z}) + f(\theta)G(\bar{z})} l. \tag{15}$$

By substituting the expressions for $f(\theta)$ and $\theta$ from Equations (2) and (14) into Equation (15), we can alternatively express the aggregate supply in the economy as a function of price

21. An increase in the reservation transportation cost increases the expected total surplus $\beta \mathbb{E}_{z'} S(z')$, since matches are less likely to be dismissed in the next period. However, such a positive effect is outweighed by the loss in the profit margin $p - \bar{z}$, resulting in a negative net effect on the total surplus.

and reservation transportation cost:

**Definition 2.** *The aggregate supply $c_s$, expressed as a function of price $p$ and reservation transportation cost $\bar{z}$, is equal to:*

$$c_s(p,\bar{z}) = \frac{\left\{1+\left[\frac{1-\eta}{\eta\rho}\left(p-\bar{z}+\beta\int_0^{\bar{z}}G(z')dz'\right)\right]^{-\xi}\right\}^{-\frac{1}{\xi}}G(\bar{z})}{1-G(\bar{z})+\left\{1+\left[\frac{1-\eta}{\eta\rho}\left(p-\bar{z}+\beta\int_0^{\bar{z}}G(z')dz'\right)\right]^{-\xi}\right\}^{-\frac{1}{\xi}}G(\bar{z})}l, \tag{16}$$

*for all $(p,\bar{z}) \in (0,+\infty)\times(0,+\infty)$ satisfying:*

$$p-\bar{z}+\beta\int_0^{\bar{z}}G(z')dz' \geq 0. \tag{17}$$

Since the aggregate supply in (16) is determined by two endogenous variables, infinitely many combinations of price and reservation transportation cost could yield the same aggregate supply, as long as they satisfy the constraint (17).[22] For the tractability of the model, we specify in Proposition 2′ a pricing mechanism in which the price of goods is flexible while the reservation transportation cost is fixed, and derive in Proposition 2 the relevant properties of the aggregate supply when such a pricing mechanism is present.[23] More importantly, since the price alone equilibrates the product market, the flexible-price mechanism enables our study of the dynamics of price in response to aggregate demand and supply shocks, which then rationalize the identification restrictions that we will impose on Impulse Response Functions (IRFs) when estimating the SVARs in the following sections.

**Definition 2′.** *For an arbitrary reservation transportation cost $\tau \in (0,+\infty)$, the flexible-price aggregate supply $c_s^{flex}$ is the function of price $p$ defined by:*

$$c_s^{flex}(p) = \frac{\left\{1+\left[\frac{1-\eta}{\eta\rho}\left(p-\tau+\beta\int_0^{\tau}G(z')dz'\right)\right]^{-\xi}\right\}^{-\frac{1}{\xi}}G(\tau)}{1-G(\tau)+\left\{1+\left[\frac{1-\eta}{\eta\rho}\left(p-\tau+\beta\int_0^{\tau}G(z')dz'\right)\right]^{-\xi}\right\}^{-\frac{1}{\xi}}G(\tau)}l, \tag{18}$$

22. This setup is similar to that in Michaillat and Saez (2015), where either price or tightness must be assumed fixed to select an equilibrium. Our model also does not allow for an equilibrium in which both the price and reservation transportation cost can be determined simultaneously. The reason is similar: each importer-household pair decides the price in a situation of bilateral monopoly. Since the solution to the bilateral monopoly problem is indeterminate (Howitt and McAfee 1987; Hall 2005), it cannot be used to impose a condition on the price.

23. We discuss in Appendix E the alternative pricing mechanism in which the price of goods is fixed while the reservation transportation cost can vary. In addition to the derivation of its key analytical properties, we apply numerical methods to approximate such a fixed-price aggregate supply and illustrate its non-standard behavior over different values of the reservation transportation cost.

*for all* $p \in [p^{min}, +\infty)$*, where* $p^{min}$ *satisfies:*

$$p^{min} - \tau + \beta \int_0^{\tau} G(z')dz' = 0.$$

**Proposition 2.** *The flexible-price aggregate supply* $c_s^{flex}$ *has the following properties:*

1. $c_s^{flex}(p^{min}) = 0$ *and* $\lim_{p\to+\infty} c_s^{flex}(p) = G(\tau)l$*;*
2. $c_s^{flex}(p)$ *is strictly increasing in* $p$ *on* $[p^{min}, +\infty)$*; and*
3. $c_s^{flex}(p)$ *is concave on* $[p^{min}, +\infty)$*.*

*Proof.* See Appendix D.2. ■

The flexible-price aggregate supply essentially represents the quantity of goods traded that satisfy (16) when $\bar{z} = \tau$. Therefore, its dynamics are solely determined by how the equilibrium product market tightness reacts to a price change. A higher price first leads to a higher total surplus. This, in turn, incentivizes importers to visit more exporters, resulting in a higher product market tightness and a greater probability for an exporter to meet an importer. Since the reservation transportation cost cannot endogenously adjust to decrease such probability, more matches are created, leading to an increase in aggregate supply.

The flexible-price aggregate supply is plotted in Figure 6, which represents the quantity of goods supplied at each price level. Figure 6 also illustrates the relationship between the flexible-price aggregate supply, its theoretical upper bound if matching frictions were absent, and productive capacity. Specifically, the flexible-price aggregate supply is an increasing and concave function of price. If there were no matching frictions, $G(\tau)l$ units of goods could be supplied. Therefore, the gap between the flexible-price aggregate supply and its theoretical upper bound represents the matching cost. Moreover, the additional quantity of goods that could be supplied if the endogenous separation of exporter-importer matches on transportation cost were also absent is $l - G(\tau)l$, so the gap between the theoretical upper bound and productive capacity represents the transportation cost (measured in units of goods). Lastly, the gap between the flexible-price aggregate supply and productive capacity measures the spare capacity of exporters. It also represents the difference between labor demand and supply, thereby providing us with a measure of unemployment in the economy.

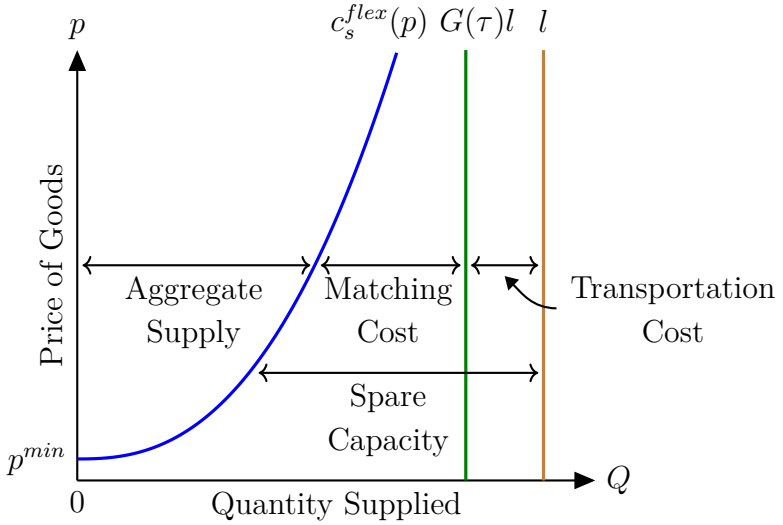



**Figure 6:** Supply Side of the Economy When the Price of Goods Is Flexible

## 3.2. Households

The representative household derives utility from consuming goods and holding real money balances.[24] The household's utility is given by:

$$u\big(c, \frac{m}{p}\big) = \frac{\chi}{1+\chi} c^{\frac{\epsilon-1}{\epsilon}} + \frac{1}{1+\chi}\big(\frac{m}{p}\big)^{\frac{\epsilon-1}{\epsilon}},$$

where $c$ denotes consumption, $m$ is the nominal money balance, $p$ is the price, the parameter $\chi > 0$ represents the taste for consumption relative to holding money, and the parameter $\epsilon > 1$ is the elasticity of substitution between consumption and real money balances.

Taking the price as given, the representative household chooses consumption and nominal money balances to maximize utility, subject to the budget constraint. The household, with an endowment $\mu > 0$ of nominal money, purchases $c$ goods at price $p$ from importers and holds $m$ units of nominal money balances. This leads to the following budget constraint:

$$pc + m \leq \mu.$$

24. We borrow the money in the utility function directly from Michaillat and Saez (2015) to ensure that aggregate demand plays a meaningful role in driving the macro aggregates. More importantly, the presence of money is necessary for studying the state-dependent effects of a contractionary monetary policy shock, as outlined in Section 5.

Solving the utility-maximization problem yields the optimal condition for the household:

$$\frac{\chi}{1+\chi}c^{-\frac{1}{\epsilon}} = \frac{1}{1+\chi}\left(\frac{m}{p}\right)^{-\frac{1}{\epsilon}}, \tag{19}$$

implying that she is indifferent between consumption and holding money at the margin.

*Aggregate Demand*. The aggregate demand in the economy is equal to the level of consumption that maximizes utility at a given price when all resources are consumed:

**Definition 3.** *The aggregate demand $c_d$ for a given price $p \in (0, +\infty)$ equals:*

$$c_d(p) = \frac{\chi^\epsilon}{1+\chi^\epsilon}\frac{\mu}{p}. \tag{20}$$

**Proposition 3.** *$c_d(p)$ is strictly decreasing and convex on $(0, +\infty)$.*

*Proof.* Direct proof from Equation (20). ■

Figure 7 in the next section shows the aggregate demand, which is downward sloping in the $(c, p)$ plane. Since a higher price leads to lower real money balances, the households' indifference between consumption and holding money implies that they would behave optimally and desire lower consumption when the price is higher. Hence, the aggregate demand in the economy decreases with the price.

## 3.3. Flexible-Price Equilibrium

With the flexible-price aggregate supply and aggregate demand sketched out, we define a flexible-price equilibrium as an equilibrium in which the reservation transportation cost is an external parameter:

**Definition 4.** *A flexible-price equilibrium parameterized by $\tau > 0$ consists of a price $p$ and a reservation transportation cost $\bar{z}$ such that the flexible-price aggregate supply equals the aggregate demand:*

$$c_s^{flex}(p) = c_d(p), \tag{21}$$

*while the reservation transportation cost is given by the parameter $\tau$, i.e., $\bar{z} = \tau$.*

**Proposition 4.** *For any $\tau > 0$, there exists a unique flexible-price equilibrium parameterized by $\tau$ that features positive price and consumption.*

*Proof.* See Appendix D.3. ■

Figure 7 depicts the flexible-price aggregate supply, the aggregate demand, and the corresponding flexible-price equilibrium. The equilibrium price is at the intersection of the flexible-price aggregate supply and aggregate demand in the $(c, p)$ plane. Both the theoretical upper bound of the flexible-price aggregate supply if the matching frictions were absent and productive capacity are also plotted in the figure for comparison.

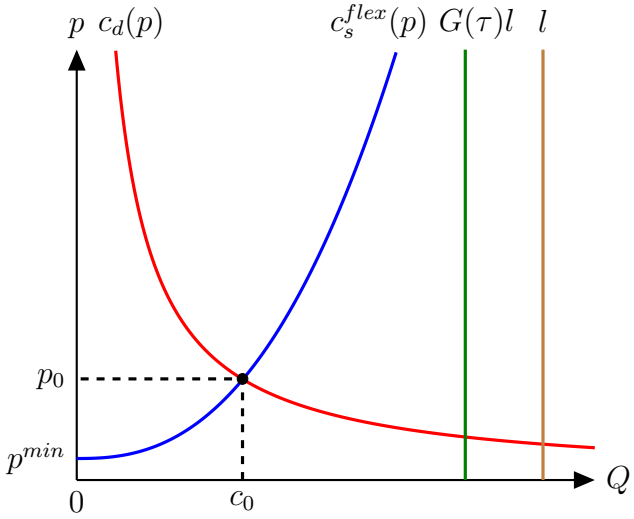



**Figure 7:** Flexible-Price Aggregate Supply, Aggregate Demand, and Flexible-Price Equilibrium

## 3.4. Comparative Statics

We use comparative statics to derive the responses of the macro aggregates to adverse shocks to demand, labor supply, and supply chain, respectively. These will provide identification restrictions for studying the causal effects of supply chain disturbances in the SVARs. In our model, an adverse shock to aggregate demand is either a decrease in the money supply, $\mu$, or in the preference for consuming goods, $\chi$. An adverse shock to labor supply is a negative disturbance to the labor supply (or equivalently, productive capacity), $l$. An adverse shock

to supply chain is a comprehensive increase in the distribution of transportation costs, encapsulated by a rise in $\gamma$, the scale parameter of the log-normal distribution of transportation costs. *Ceteris paribus*, an increase in $\gamma$ implies a higher average transportation cost, i.e., $exp(\gamma + \sigma^2/2)$. Proposition 5 summarizes the responses of the macro aggregates to these distinct shocks.[25]

**Proposition 5.** *In equilibrium:*

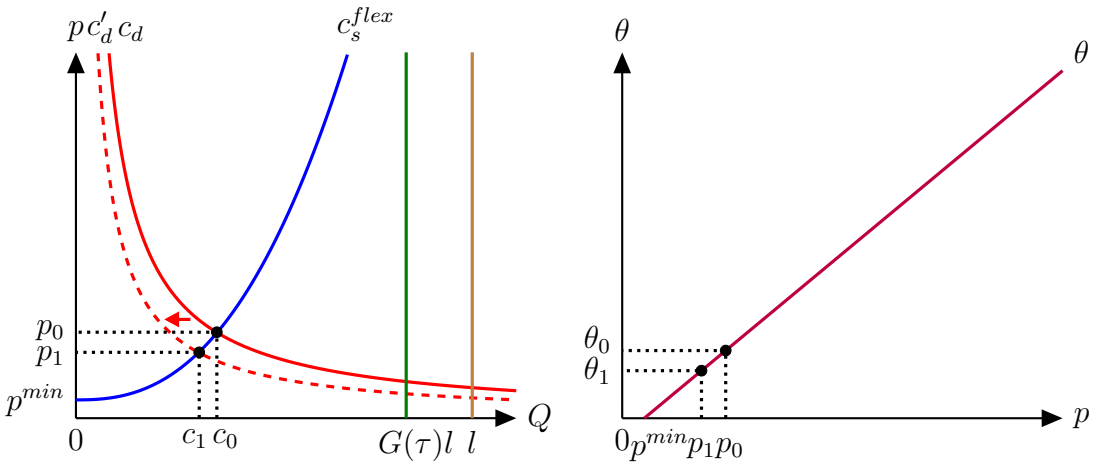
- ***An adverse shock to aggregate demand*** *increases matching cost and spare capacity (or equivalently, unemployment), while it decreases consumption (or equivalently, output), price, product market tightness, and import price.*
- ***An adverse shock to labor supply*** *increases price, product market tightness, and import price, while it decreases consumption (or equivalently, output), matching cost, and spare capacity (or equivalently, unemployment).*
- ***An adverse shock to supply chain*** *increases price and spare capacity (or equivalently, unemployment), while it decreases consumption (or equivalently, output). The responses of product market tightness, import price, and matching cost are undetermined.*

*Proof.* See Appendix D.4. ■

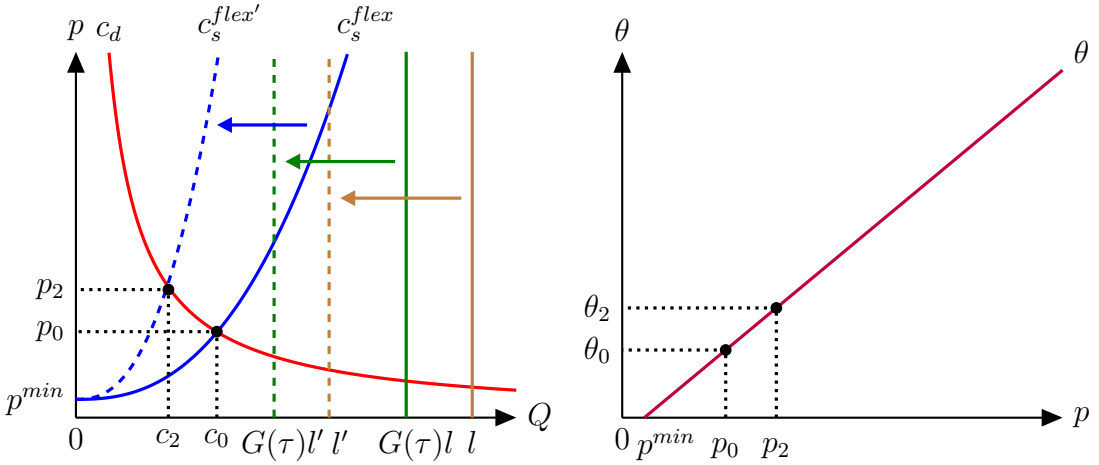
Table 1 summarizes the signs of the responses of the macro aggregates to the three different shocks. Figure 8 also illustrates the comparative statics graphically (left panels), alongside the corresponding equilibrium condition between product market tightness and price (right panels) from Equation (14). Such a condition describes the optimal interplay between product market tightness and price.

Panel (a) in Figure 8 shows the response of the system to a decline in aggregate demand. The aggregate demand curve shifts inwards, driven by the preference for lower consumption by households, either because they hold less money or they prefer to consume less. In equilibrium, the price decreases to clear the market. As the price decreases, importers

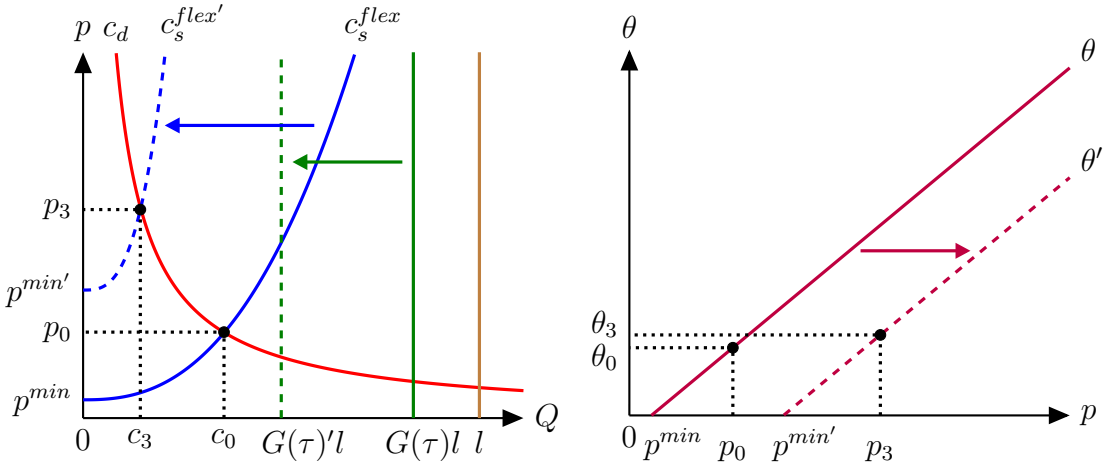
25. Unlike Michaillat and Saez (2015) in which there is a matching cost that differentiates consumption from output, consumption and output are equivalent in our model.




**(a)** An Adverse Shock to Aggregate Demand, i.e., $\mu \downarrow$ or $\chi \downarrow$




**(b)** An Adverse Shock to Labor Supply, i.e., $l \downarrow$




**(c)** An Adverse Shock to Supply Chain, i.e., $\gamma \uparrow$

**Figure 8:** Graphical Representation of Comparative Statics

**Table 1:** Comparative Statics for Adverse Shocks to Aggregate Demand, Labor Supply, and Supply Chain

| **Adverse Shock To:** | **Effects On:** | | | | | |
|---|---|---|---|---|---|---|
| | Consumption (or Output) $c$ | Price $p$ | Product Market Tightness $\theta$ | Import Price $r$ | Matching Cost $G(\tau)l - c$ | Spare Capacity (or Unemployment) $l - c$ |
| Aggregate Demand | $-$ | $-$ | $-$ | $-$ | $+$ | $+$ |
| Labor Supply | $-$ | $+$ | $+$ | $+$ | $-$ | $-$ |
| Supply Chain | $-$ | $+$ | N/A | N/A | N/A | $+$ |

*Notes.* The table summarizes the comparative statics in Proposition 5. An adverse shock to aggregate demand is a decrease in money supply, $\mu$, or in the taste for consumption of goods, $\chi$. An adverse shock to labor supply is a decrease in labor supply (or equivalently, productive capacity), $l$. An adverse shock to supply chain is an increase in the scale parameter of the log-normal distribution of transportation costs, $\gamma$.

visit fewer exporters to participate in trade, hence lowering product market tightness. The declines in price and product market tightness then contribute to a lower import price, as not only does a trade itself become less profitable, but also the probability of getting into a trade for an importer becomes higher, since congestion weakens. Consequently, exporters sell a lower fraction of their productive capacity to importers, resulting in a decrease in consumption (or equivalently, output). This leads to an increase in matching cost and spare capacity (or equivalently, unemployment).

Panel (b) in Figure 8 shows the response of the system to a negative labor supply shock that decreases productive capacity.[26] The negative shock to the aggregate supply causes it to rotate inwards while leaving $p^{min}$ unchanged. The price increases to clear the market, and consumption (or equivalently, output) decreases as the equilibrium moves upwards along the aggregate demand curve. The increase in the price raises product market tightness. This simultaneous rise in price and product market tightness leads to a higher import price. Along with the contraction in productive capacity, this results in lower matching costs and reduced spare capacity (or equivalently, unemployment).

Lastly, Panel (c) in Figure 8 shows the response of the system to an increase in transportation costs corresponding to a negative supply chain shock, encapsulated by the increase

26. This shock is commonly termed as a "supply shock" and has been studied intensively in the literature. See, for instance, del Rio-Chanona et al. (2020), Bonadio et al. (2021), Brinca, Duarte, and Faria-e-Castro (2021), and Leyva and Urrutia (2022).

in the scale parameter of the log-normal distribution of transportation costs. The increase generates a higher mean transportation cost, increasing the probability of drawing a transportation cost above the reservation threshold. Since the reservation threshold is fixed, the expected total surplus from a trade decreases without a change in the price. To continue benefiting from trade, importers raise the price of imported goods to households and pass on these costs to consumers. Consequently, the price rises while consumption (or equivalently, output) falls. Graphically, this process is represented by an inward shift of the aggregate supply curve, and unlike in the negative labor supply shock, $p^{min}$ increases in response to the shock. Since the productive capacity (or equivalently, labor supply) is fixed, spare capacity (or equivalently, unemployment) increases in response to the negative supply chain shock.

In terms of the effect on product market tightness, as seen in Equation (22),

$$\theta(\gamma) = \frac{1-\eta}{\eta\rho}\Big[\underbrace{p(\gamma)-\tau}_{\text{Profit Margin }\uparrow} + \underbrace{\beta\int_0^{\tau}\Phi(\frac{\log z'-\gamma}{\sigma})dz'}_{\text{Expected Total Surplus }\downarrow}\Big], \tag{22}$$

the result remains ambiguous. On the one hand, an increase in $\gamma$ reduces the expected total surplus, since it becomes more likely to obtain a bad draw that severs trade. On the other hand, an increase in $\gamma$ raises the price, and thus, the profit margin. Therefore, if the price rises to a level that offsets the negative effect of a lower expected total surplus, product market tightness will increase, as depicted in Panel (c) of Figure 8. Alternatively, if the price increase is insufficient to reverse the aforementioned relationship, product market tightness will decrease accordingly.

Lastly, as discussed in Appendix D.4, the corresponding changes in import price and matching cost depend on how the price and product market tightness evolve following an adverse shock to supply chain. Therefore, their comparative statics also remain ambiguous.

# 4. The Causal Effects of Supply Chain Disruptions

In this section, we study the causal effects of supply chain disruptions by developing an SVAR model that restricts the responses of the macro aggregates according to our theoretical results

and uses our new ACR index.[27] We also highlight the differences between our index and the alternative GSCPI index, and study the implications of these differences on the statistical significance of supply chain disruption shocks during the Covid-19 pandemic.

## 4.1. A SVAR Model With Sign and Zero Restrictions

Our model is based on Rubio-Ramirez, Waggoner, and Zha (2010) and Arias, Rubio-Ramirez, and Waggoner (2018):

$$\boldsymbol{y}_t'\boldsymbol{A}_0 = \sum_{l=1}^{L} \boldsymbol{y}_{t-l}'\boldsymbol{A}_l + \boldsymbol{\omega}_t'\boldsymbol{C} + \boldsymbol{\epsilon}_t', \quad 1 \leq t \leq T, \tag{23}$$

where $\boldsymbol{y}_t$ is an $n \times 1$ vector of endogenous variables, $\boldsymbol{\omega}_t = [1, t]'$ is a $2 \times 1$ vector of a constant and a linear trend, $\boldsymbol{\epsilon}_t$ is an $n \times 1$ vector of structural shocks, $\boldsymbol{A}_l$ is an $n \times n$ matrix of structural parameters for $0 \leq l \leq L$ with $\boldsymbol{A}_0$ invertible, $\boldsymbol{C}$ is a $2 \times n$ matrix of parameters, $L$ is the lag length, and $T$ is the sample size. The vector $\boldsymbol{\epsilon}_t$, conditional on past information and the initial conditions $\boldsymbol{y}_0, \ldots, \boldsymbol{y}_{1-L}$ is Gaussian with mean zero and covariance matrix $\mathbf{1}_{n\times n}$, i.e., the $n \times n$ identity matrix. The SVAR described in Equation (23) can be written compactly as:

$$\boldsymbol{y}_t'\boldsymbol{A}_0 = \boldsymbol{x}_t'\boldsymbol{A}_+ + \boldsymbol{\epsilon}_t', \quad 1 \leq t \leq T, \tag{24}$$

where $\boldsymbol{A}_+' = [\boldsymbol{A}_1' \ \ldots \ \boldsymbol{A}_L' \ \boldsymbol{C}']$ and $\boldsymbol{x}_t' = [\boldsymbol{y}_{t-1}' \ \ldots \ \boldsymbol{y}_{t-L}' \ \boldsymbol{\omega}_t']$ for $1 \leq t \leq T$. The dimension of $\boldsymbol{A}_+$ is $m \times n$, where $m = nL + 2$. The reduced-form representation implied by Equation (24) is given by:

$$\boldsymbol{y}_t' = \boldsymbol{x}_t'\boldsymbol{B} + \boldsymbol{u}_t', \quad 1 \leq t \leq T,$$

where $\boldsymbol{B} = \boldsymbol{A}_+\boldsymbol{A}_0^{-1}, \boldsymbol{u}_t' = \boldsymbol{\epsilon}_t'\boldsymbol{A}_0^{-1}$, and $\mathbb{E}(\boldsymbol{u}_t\boldsymbol{u}_t') = \boldsymbol{\Sigma} = (\boldsymbol{A}_0\boldsymbol{A}_0')^{-1}$. The matrices $\boldsymbol{B}$ and $\boldsymbol{\Sigma}$ are the reduced-form parameters, while $\boldsymbol{A}_0$ and $\boldsymbol{A}_+$ are the structural parameters.

We estimate the model using the monthly U.S. series of real GDP, GDP deflator, unemployment, import price, as well as our ACR index over the period from January 2017 to

27. When we disentangle the causal effects of a supply chain disruption shock from others, it is important to include the relevant variable(s) necessary for identification in the econometric models. This step is crucial to prevent the omitted variable bias, which could introduce a serious flaw in certain scenarios. For instance, an oil price shock could influence real GDP, inflation, and unemployment similarly to a supply chain disruption shock (Känzig 2021; Gagliardone and Gertler 2023).

July 2022, with all series being seasonally adjusted. All the variables are from the Federal Reserve Economic Data (FRED), maintained by the Federal Reserve Bank of St. Louis.[28] The real GDP, GDP deflator, and import price are in log percent, while the unemployment and ACR are in percent. We set the number of lags to two in the baseline specification, but the results are robust to considering one or three lags.[29]

Our identification scheme applies the sign restrictions from our theoretical model, which are summarized in Table 1, as well as the zero restrictions on the responses of the ACR index to adverse aggregate demand and labor supply shocks. We estimate the SVAR using a Bayesian approach as in Arias, Rubio-Ramirez, and Waggoner (2018), Arias, Caldara, and Rubio-Ramírez (2019), and Arias et al. (2023) with restrictions on the first period of response (i.e., $k = 1$), thus imposing a minimal structure as in Mumtaz and Zanetti (2012, 2015).[30] More concretely, we impose the following restrictions:

**Restriction 1.** ***An adverse shock to aggregate demand*** *leads to a negative response of real GDP, GDP deflator, and import price, as well as to a positive response of unemployment at $k = 1$. ACR does not respond at $k = 1$.*

**Restriction 2.** ***An adverse shock to labor supply*** *leads to a negative response of real GDP and unemployment, as well as to a positive response of GDP deflator and import price at $k = 1$. ACR does not respond at $k = 1$.*

**Restriction 3.** ***An adverse shock to supply chain*** *leads to a negative response of real GDP, as well as to a positive response of GDP deflator, unemployment, and ACR at $k = 1$.*

28. The mnemonics of the variables are: `GDPC1` (real GDP), `INDPRO` (industrial production), `GDPDEF` (GDP implicit price deflator), `CPIAUCSL` (consumer price index), `PPIFG` (producer price index), `UNRATE` (unemployment), and `IREXFDFLS` (import price). The monthly time series for real GDP and GDP deflator are constructed using interpolation of the corresponding quarterly time series, as in Bernanke and Mihov (1998) and Arias, Caldara, and Rubio-Ramírez (2019). Specifically, we apply the Chow-Lin method for temporal disaggregation (Chow and Lin 1971) to interpolate the real GDP based on the industrial production index, while interpolating the GDP deflator based on the consumer price index and the producer price index. The unemployment and import price are raw series from the U.S. Bureau of Labor Statistics.

29. Appendix F.1 demonstrates the robustness of our baseline results when considering different lag structures and extended horizons to impose the sign restrictions on IRFs.

30. We impose a normal-generalized-normal (NGN) prior distribution over the structural parameters $\boldsymbol{A}_0$ and $\boldsymbol{A}_+$. The NGN prior is a conjugate prior characterized by four parameters $(\nu, \boldsymbol{\Phi}, \boldsymbol{\Psi}, \boldsymbol{\Omega})$. The parameters $\nu$ and $\boldsymbol{\Phi}$ govern the marginal prior distribution of $vec(\boldsymbol{A}_0)$, while the remaining parameters $\boldsymbol{\Psi}$ and $\boldsymbol{\Omega}$ govern the prior distribution of $vec(\boldsymbol{A}_+)$, conditional on $\boldsymbol{A}_0$. Our choice of the prior density parameterization is $\nu = 0, \boldsymbol{\Phi} = \boldsymbol{0}_{n\times n}, \boldsymbol{\Psi} = \boldsymbol{0}_{m\times n}$, and $\boldsymbol{\Omega}^{-1} = \boldsymbol{0}_{m\times m}$. This parameterization generates prior densities that are equivalent to those in Uhlig (2005). Nevertheless, as illustrated in Appendix F.4, our results are robust to using the prior robust approach in Giacomini and Kitagawa (2021).

Figures 9, 10, and 11 present our baseline results for the responses of the endogenous variables to an adverse shock to aggregate demand, labor supply, and the supply chain respectively. The solid line shows the point-wise posterior median IRFs of the endogenous variables to each structural shock, and the gray-shaded bands represent the corresponding 68% and 90% posterior probability bands.[31] We start by discussing the IRFs to an adverse shock to aggregate demand in Figure 9. On impact, real GDP declines significantly by approximately 1.0%, while unemployment rises sharply by more than 0.5%. Such responses persist with a high posterior probability for the first six months after the shock. In contrast, the response of the GDP deflator is more muted, with its initial fall sitting at -0.1% before gradually reverting back to zero after a one-year window. Import price exhibits a similar pattern, although a zero response emerges much sooner at the six-month mark. Lastly, the response of the ACR index is less precisely estimated, with a large posterior probability mass centered around zero.

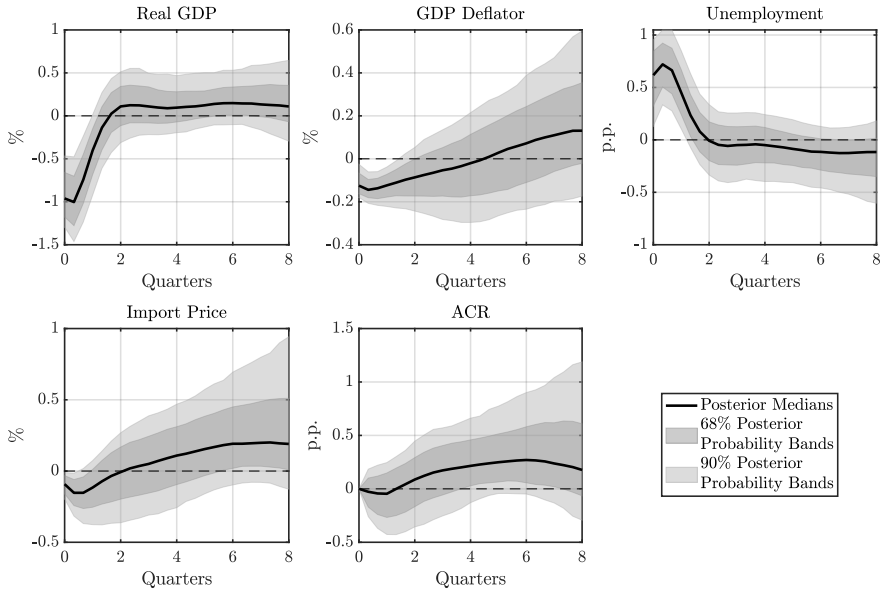



**Figure 9:** IRFs to an Adverse Shock to Aggregate Demand: Baseline

*Notes.* The IRFs to a one standard deviation adverse shock to aggregate demand are identified using the ACR index and Restrictions 1, 2, and 3. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. The figure is based on 100,000 independent draws.

31. The results are based on 100,000 independent draws from the posterior distribution of the structural parameters, and the structural shocks are of size one standard deviation.

Figure 10 shows the IRFs to an adverse shock to labor supply. On impact, following Restriction 2, both the responses of real GDP and unemployment are negative. Subsequently, real GDP continues to fall, with a zero response almost at the boundary of the 90% confidence set near the trough, which occurs about three months after the shock. Largely due to such a fall in real GDP, the initial decline in unemployment is quickly reversed, and it turns significantly positive within one quarter from the shock, peaking at approximately 0.3% before reverting back to zero. The GDP deflator increases and remains elevated for approximately one year, reflecting the lag effects of supply-side shocks. Import price again exhibits a similar pattern, but the peak is reached at a much earlier horizon. Lastly, the median response of ACR is zero on impact and consistently above zero for almost one year afterwards.

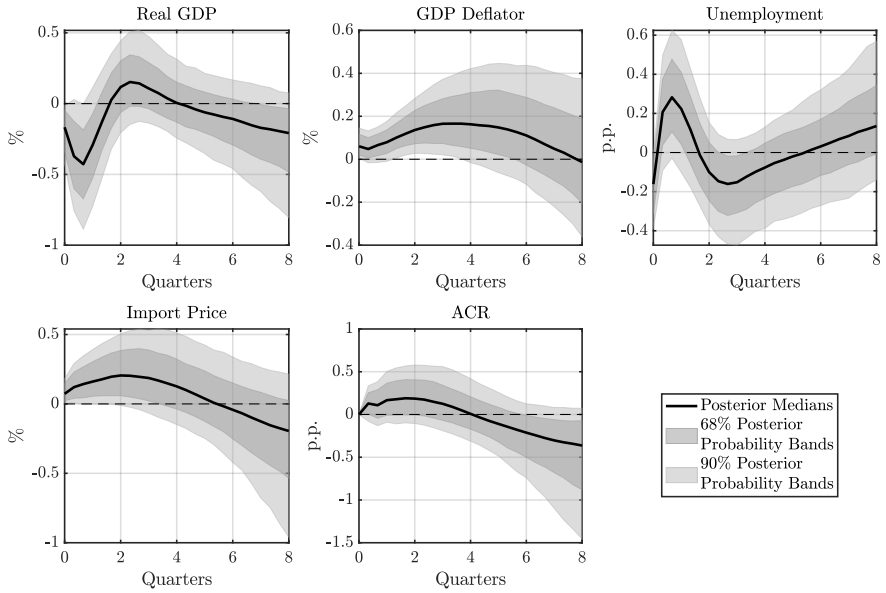



**Figure 10:** IRFs to an Adverse Shock to Labor Supply: Baseline

*Notes.* The IRFs to a one standard deviation adverse shock to labor supply are identified using the ACR index and Restrictions 1, 2, and 3. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. The figure is based on 100,000 independent draws.

Finally, Figure 11 shows the IRFs to a negative shock to the supply chain. The median response of real GDP is negative on impact, and it remains below zero for more than one quarter after the shock. The response of unemployment mirrors that of real GDP, albeit with a smaller magnitude. The increases in both the GDP deflator and import price align

with the magnitude observed in the labor supply shock, highlighting the significant role of supply chain disruptions in driving up prices. Lastly, the response of the ACR index remains elevated for nearly one year after the shock.

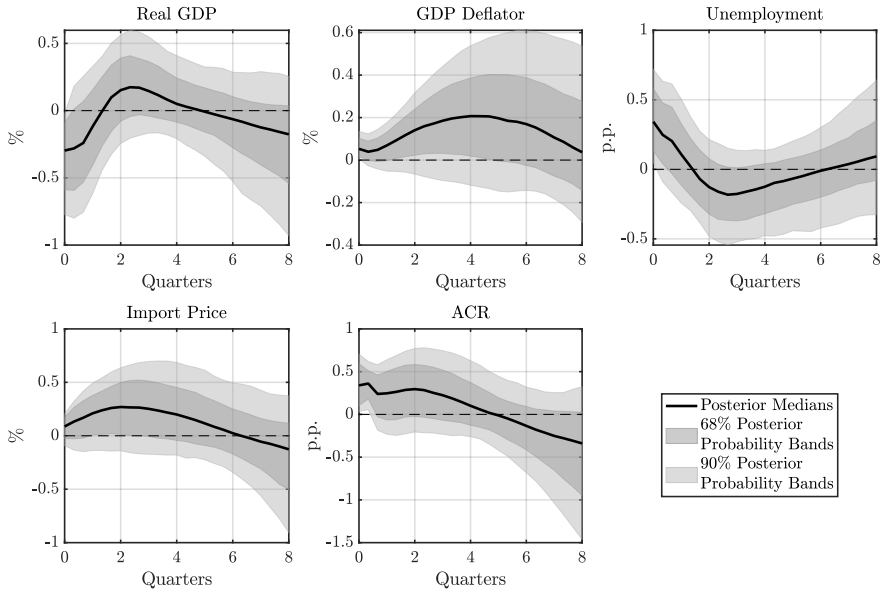



**Figure 11:** IRFs to an Adverse Shock to Supply Chain: Baseline

*Notes.* The IRFs to a one standard deviation adverse shock to supply chain are identified using the ACR index and Restrictions 1, 2, and 3. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. The figure is based on 100,000 independent draws.

## 4.2. Comparison Between the ACR and GSCPI

In this section, we assess the implications of the differences between the ACR and GSCPI indices for the readings that the SVAR model makes regarding the causal effect of supply chain disruptions on inflation by studying: (i) IRFs to an adverse shock to supply chain, (ii) Forecast Error Variance Decomposition (FEVD), and (iii) Historical Decomposition (HD), using our empirical model and the sign and zero restrictions developed in Section 4.1.[32] As illustrated in Section 2.3, we find that the behaviors of the two indices diverge significantly from early 2020 onwards, and the substantial increase in the GSCPI at the onset of the Covid-19 pandemic is likely driven by sudden changes in demand and the management's

32. As a robustness check, Appendix F.2 estimates a version of the model without the zero restrictions imposed on the GSCPI, and the comparison results remain unchanged.

mis-perception of supply chain issues as recorded by the PMI surveys.

Figure 12 shows the IRFs to an adverse shock to supply chain for the GSCPI index. The responses of real GDP and unemployment closely resemble the baseline responses when we use the ACR index (Figure 11). The responses of the GDP deflator and import price are around zero and statistically insignificant, and the response of the GSCPI is positive on impact, returning to zero after the one-quarter mark.

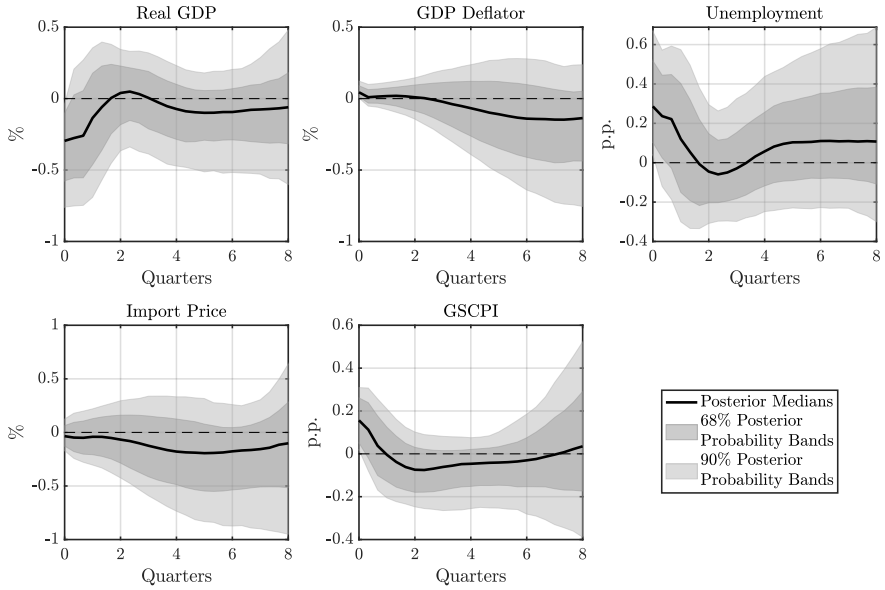
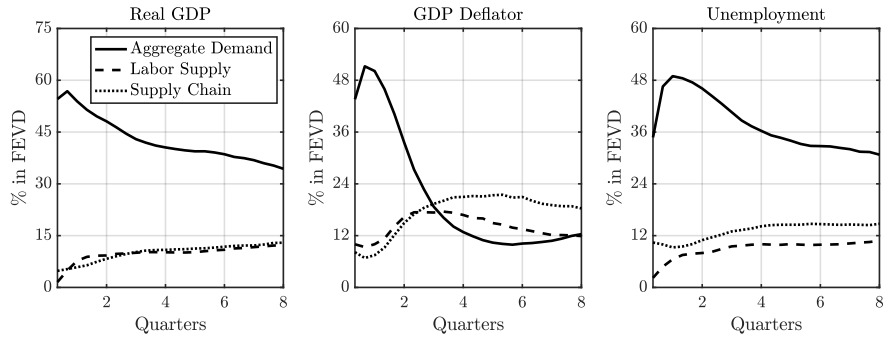


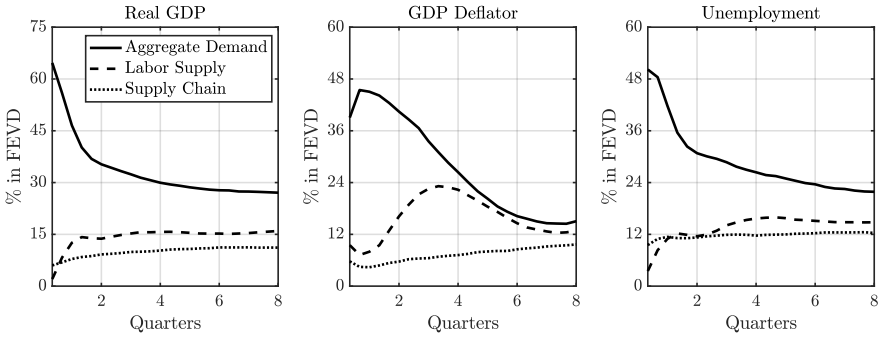

**Figure 12:** IRFs to an Adverse Shock to Supply Chain: The GSCPI and Restrictions 1, 2, and 3

*Notes.* The IRFs to a one standard deviation adverse shock to supply chain are identified using the GSCPI index and Restrictions 1, 2, and 3. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. This figure is based on 100,000 independent draws.

Figures 13a and 13b illustrate the proportion of the forecast error variance explained by each of the three structural shocks, using the ACR and GSCPI indices, respectively. A comparison of the two figures reveals that aggregate demand shocks account for the largest fraction of unexpected fluctuations in real GDP and unemployment for both indices. However, the supply chain shock explains a significant fraction of the unexpected fluctuations in the GDP deflator at longer horizons for the ACR index, while it only accounts for a minimal fraction for the GSCPI index. This latter finding is consistent with the zero response of the GDP deflator to the supply chain shock for the GSCPI index (Figure 12).




**(a)** Baseline




**(b)** The GSCPI and Restrictions 1, 2, and 3

**Figure 13:** FEVD from the SVAR

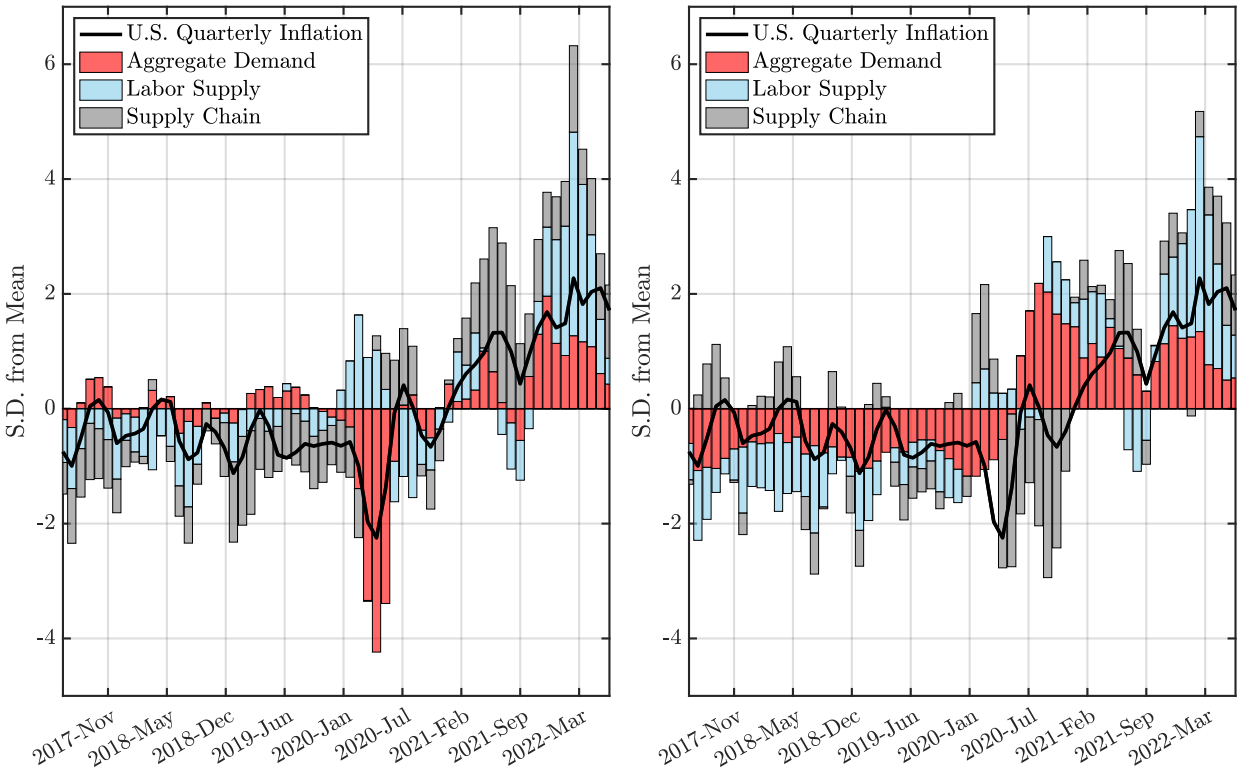
*Notes.* Each line presents the median fraction of the forecast error variance for each endogenous variable, explained by each of the three identified structural shocks at various time horizons. The FEVD is estimated using the ACR/GSCPI index and Restrictions 1, 2, and 3, and based on 100,000 independent draws.

Finally, Figures 14a and 14b show the cumulative historical contribution of each of the three structural shocks to U.S. inflation for the ACR and GSCPI indices, respectively.[33] Our ACR index attributes the initial fall in inflation at the onset of the Covid-19 pandemic to a decline in demand, and the subsequent rise in inflation from April 2020 to adverse shocks to the supply chain, which remain influential for inflation over the sample period. Interestingly, our model shows that supply chain disturbances consistently exert a negative contribution to inflation prior to the global pandemic period that started in March 2020.[34] In contrast,

33. To facilitate comparison of the series across different scales, we apply Z-score standardization, which re-scales data to have a mean of zero and a standard deviation of one.

34. The persistent negative contribution of shocks to the supply chain to inflation supports the political motives for the enhancements of supply chain operations to ease inflationary pressures. Several U.S. ports underwent considerable infrastructure upgrades in the period 2017-2019 and the U.S. Congress enacted the Resilient Ports Act in 2021.

the results based on the GSCPI index attribute the early fall in inflation to positive shocks to the supply chain, while the rise in inflation subsequent to the onset of the pandemic is principally explained by demand shocks.




**(a)** Baseline **(b)** The GSCPI and Restrictions 1, 2, and 3

**Figure 14:** HD of the GDP Deflator

*Notes.* In both panels, the solid line represents the standardized quarterly inflation rate in the U.S., i.e., Q-on-Q growth of the GDP deflator. The shaded bar represents the standardized cumulative historical contribution of each of the three structural shocks identified using the ACR/GSCPI index and Restrictions 1, 2, and 3 to the U.S. inflation. The estimation results are obtained with each variable measured in percent change from the previous period, and are calculated based on 100,000 independent draws.

Taken together, we find significant differences between the ACR and GSCPI indices and show that they provide contrasting interpretations of the contributions of different shocks to inflation over the sample period.

# 5. The Effectiveness of Monetary Policy

In this section, we study the interplay between supply chain disruptions and the changes in the effectiveness of monetary policy to control inflation and output. We show in our theoretical model that disruption to the supply chain increases the sensitivity of inflation and reduces the sensitivity of output to a contractionary monetary policy shock, generating state-dependence that changes the tradeoff in monetary policy. We then test and corroborate the theoretical prediction using a Threshold Vector Autoregression (TVAR) model.

## 5.1. Theoretical Prediction

We derive the theoretical prediction for the state-dependence of monetary policy using our model described in Section 3. The monetary supply parameter $\mu$ encapsulates the action of monetary policy, and the transportation cost parameter $\gamma$ captures the disruption to the supply chain. We study the comparative statics of the impact of a tightening in monetary policy, focusing on whether the effects of the policy intervention on inflation and output are different amid the supply chain disruption. The results are summarized in Proposition 6.

**Proposition 6.** *For any given threshold of transportation cost $\tau > 0$ and parameter values $\mu \in \mathbb{R}^+$ and $\gamma \in \mathbb{R}$ such that the following constraint holds:*

$$\frac{\partial \theta(\mu,\gamma)}{\partial \gamma} > \frac{\theta(1+\theta^{\xi})}{\big(1-G(\tau)\big)G(\tau)} \frac{1}{\sigma\sqrt{2\pi}} \exp\Big[-\frac{(\log\tau-\gamma)^2}{2\sigma^2}\Big], \tag{25}$$

*where $G(\tau) \equiv \Phi[(\log\tau-\gamma)/\sigma]$, $\Phi(.)$ is the standard normal cumulative density function, the responses of the endogenous variables to a change in monetary policy are described by the partial derivatives:*

$$\frac{\partial c(\mu,\gamma)}{\partial \mu} > 0, \ \frac{\partial p(\mu,\gamma)}{\partial \mu} > 0, \ \frac{\partial \theta(\mu,\gamma)}{\partial \mu} > 0, \ \frac{\partial r(\mu,\gamma)}{\partial \mu} > 0,$$
$$\frac{\partial}{\partial \mu}\big[G(\tau)l - c(\mu,\gamma)\big] < 0, \ \frac{\partial}{\partial \mu}\big[l - c(\mu,\gamma)\big] < 0.$$

*The cross derivatives that describe the variation in the responses of the endogenous variables*

*ascribed to the supply chain disruption satisfy:*

$$\frac{\partial^2 c(\mu,\gamma)}{\partial\mu\partial\gamma} < 0,\ \frac{\partial^2 p(\mu,\gamma)}{\partial\mu\partial\gamma} > 0,\ \frac{\partial^2 \theta(\mu,\gamma)}{\partial\mu\partial\gamma} > 0,\ \frac{\partial^2 r(\mu,\gamma)}{\partial\mu\partial\gamma} > 0,$$
$$\frac{\partial^2}{\partial\mu\partial\gamma}\big[G(\tau)l - c(\mu,\gamma)\big] > 0,\ \frac{\partial^2}{\partial\mu\partial\gamma}\big[l - c(\mu,\gamma)\big] > 0,$$

*where $c, p, \theta, r, G(\tau)l - c$, and $l - c$ represent consumption (or equivalently, output), price, product market tightness, import price, matching cost, and spare capacity (or equivalently, unemployment), respectively.*

*Proof.* See Appendix D.5. ■

In words, the partial and cross derivatives in Proposition 6 imply that at an equilibrium where the product market tightness is sufficiently reactive to the supply chain disruption, the contractionary monetary policy shock induces a smaller decrease in consumption (or equivalently, output) and a larger decrease in price, as evinced by the second derivatives.[35]

Figure 15 provides a graphical representation of our theoretical prediction. In response to a contractionary monetary policy shock, households reduce consumption at a given price level due to decreased money holdings. This causes the aggregate demand curve to shift inwards, leading to a reduced price and lower consumption of goods. Consequently, product market tightness diminishes as importers visit fewer exporters for trade. This reduction in price and product market tightness subsequently results in a lower import price. Exporters, in turn, sell a smaller fraction of their productive capacity to importers, leading to a decrease in output. Correspondingly, matching costs and spare capacity (or equivalently, unemployment) experience an increase.

In scenarios where the economy undergoes the supply chain disruption, the likelihood that a randomly drawn transportation cost will fall below the reservation transportation cost is minimal. This suggests that, given a certain number of meetings between exporters and importers, a significant fraction of these meetings will not proceed, thereby reducing the number of successful matches. In response to decreased demand brought on by a contractionary monetary policy shock, this necessary reduction in matches is likely to be driven

35. Proposition 6 also shows that the responses of product market tightness and import price are greater while the responses of matching cost and spare capacity (or equivalently, unemployment) are weaker during the supply chain disruption.

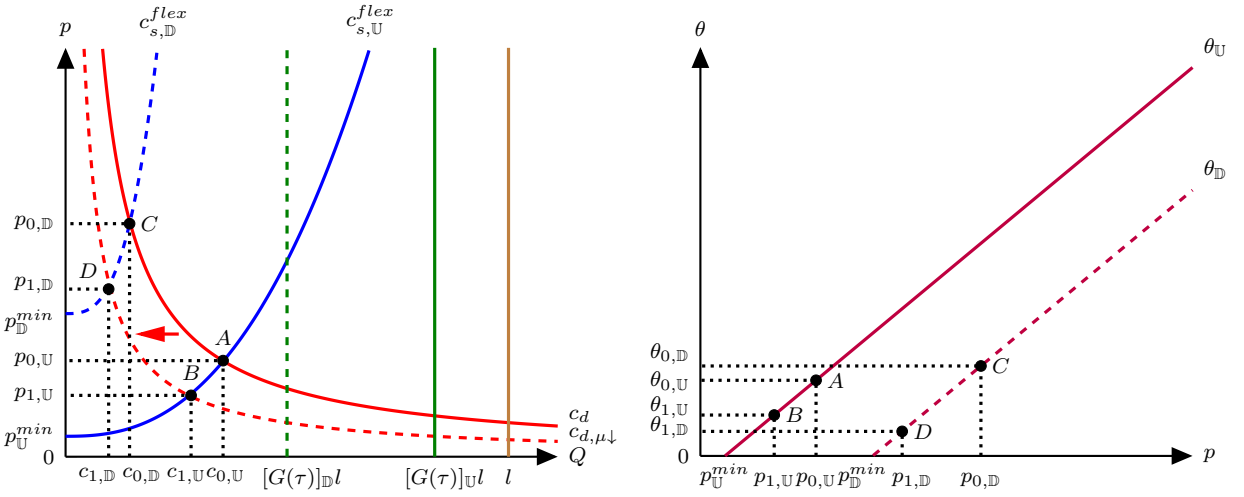



**Figure 15:** State-Dependent Effects of a Contractionary Monetary Policy Shock: Theoretical Prediction

*Notes.* The two figures illustrate how in theory the economy adjusts to a contractionary monetary policy shock and how such an adjustment depends on whether the supply chain is disrupted or not. The two respective states – i.e., supply chain disrupted ($\mathbb{D}$) versus undisrupted ($\mathbb{U}$) – are plotted against each other. $c^{flex}_{s,\mathbb{D}}$ and $c^{flex}_{s,\mathbb{U}}$ represent the flexible-price aggregate supply curves in the two states, while $\theta_{\mathbb{D}}$ and $\theta_{\mathbb{U}}$ represent the schedules of product market tightness in the two states. $c_d$ and $c_{d,\mu\downarrow}$ represent the aggregate demand curves before and after the contractionary monetary policy shock. The labels on the axes corresponding to each state are differentiated by their subscripts, and the capital letters ($A \to B, C \to D$) are also included to facilitate comparison between the two states.

by a more substantial decrease in the number of meetings between exporters and importers. Consequently, the decline in product market tightness must be more significant. To instigate such a pronounced decrease in product market tightness, prices must experience a more dramatic drop. Taken together, these dynamics suggest that supply chain disruptions enhance the sensitivity of prices to fluctuations in goods supply. This heightened sensitivity becomes notably significant when product market tightness proves to be more reactive to the supply chain disruption, as outlined in the constraint (25) of Proposition 6.

Subsequently, these more pronounced decreases in price and product market tightness will result in a more significant drop in the import price. Furthermore, since changes in consumption (or equivalently, output) inversely mirror those in price, a steeper decline in price will be paralleled by a less substantial drop in consumption (or equivalently, output). Accordingly, the increases in matching cost and spare capacity (or equivalently, unemployment) will be smaller when responding to a contractionary monetary policy shock.

## 5.2. Empirical Validation

We test the empirical prediction of the state-dependence of monetary policy by developing a structural TVAR model – building on Chen and Lee (1995) – that allows for endogenous variation in the estimated parameters based on the estimated threshold of our ACR index. The reduced-form model is the following:

$$\boldsymbol{y}_t = I_t\Big[\sum_{l=1}^{L}\boldsymbol{B}'_{\mathbb{D},l}\boldsymbol{y}_{t-l} + \boldsymbol{C}'_{\mathbb{D}}\boldsymbol{\omega}_t + \boldsymbol{\Sigma}_{\mathbb{D}}^{1/2}\boldsymbol{\epsilon}_t\Big] + (1-I_t)\Big[\sum_{l=1}^{L}\boldsymbol{B}'_{\mathbb{U},l}\boldsymbol{y}_{t-l} + \boldsymbol{C}'_{\mathbb{U}}\boldsymbol{\omega}_t + \boldsymbol{\Sigma}_{\mathbb{U}}^{1/2}\boldsymbol{\epsilon}_t\Big], \quad (26)$$

where $1 \leq t \leq T$, $\boldsymbol{y}_t$ is an $n \times 1$ vector of endogenous variables, $\boldsymbol{\omega}_t = [1, t]'$ is a $2 \times 1$ vector of a constant and a linear trend, $\boldsymbol{\epsilon}_t$ is an $n \times 1$ vector of structural shocks, $\boldsymbol{B}_{\mathbb{D},l}$ and $\boldsymbol{B}_{\mathbb{U},l}$ are two $n \times n$ matrices of coefficients for the lagged endogenous variables $\boldsymbol{y}_{t-l}$, $\boldsymbol{C}_{\mathbb{D}}$ and $\boldsymbol{C}_{\mathbb{U}}$ are two $2 \times n$ matrices of coefficients for the constant and linear trend, $\boldsymbol{\Sigma}_{\mathbb{D}}$ and $\boldsymbol{\Sigma}_{\mathbb{U}}$ are the covariance matrices, $L$ is the lag length, and $T$ is the sample size.[36] The vector $\boldsymbol{\epsilon}_t$, conditional on past information and the initial conditions $\boldsymbol{y}_0, \ldots, \boldsymbol{y}_{1-L}$, is Gaussian with mean zero and covariance matrix $\mathbf{1}_{n\times n}$, i.e., an $n \times n$ identity matrix. Switches between the two regimes – i.e., supply chain disrupted ($\mathbb{D}$) vs. undisrupted ($\mathbb{U}$) – are governed by the indicator variable $I_t \in \{0, 1\}$, which is equal to one if the ACR in period $t-1$, $ACR_{t-1}$, is above the threshold $\overline{ACR}$, and equal to zero otherwise:

$$I_t = \begin{cases} 1, & \text{if } ACR_{t-1} > \overline{ACR}; \\ 0, & \text{if } ACR_{t-1} \leq \overline{ACR}. \end{cases} \quad (27)$$

Under the Normal-Inverse-Wishart conjugate prior for the TVAR parameters and conditional on the value of the threshold $\overline{ACR}$, the posterior distribution of the TVAR parameter vector is a conditional Normal-Inverse-Wishart distribution, and we use the Gibbs sampler to draw from the distribution. Since the posterior distribution of the threshold $\overline{ACR}$ conditional on the TVAR parameters is unknown, we use a Metropolis-Hastings algorithm to obtain its posterior distribution, similar to Chen and Lee (1995), Lopes and Salazar (2006), and Pizzinelli, Theodoridis, and Zanetti (2020). Appendix G.1 provides the details on the Normal-Inverse-Wishart prior.

36. Note that we allow the covariance matrix to be regime-specific.

To retain comparability with the previous analysis, we include the same variables used in the SVAR model in Section 4.1, plus the Federal Funds Rate to reflect changes in the stance of monetary policy, and we retain the same sample period 2017M1-2022M7.[37]

To identify the contractionary monetary policy shock, we impose the following standard restriction on IRFs:

**Restriction 4.** ***A contractionary monetary policy shock*** *leads to a negative response of real GDP, GDP deflator, and import price, as well as to a positive response of unemployment and Federal Funds Rate at* $k = 1$*. ACR does not respond at* $k = 1$*.*[38]

We compute the identified set of IRFs using the Bayesian approach similar to Pizzinelli, Theodoridis, and Zanetti (2020) and Bratsiotis and Theodoridis (2022).[39] We use one lag in the baseline estimation, and select the one-month lag of the ACR index as the variable determining the state $I_t$.[40]

Figure 16 plots the IRFs to a contractionary monetary policy shock for both the supply chain disrupted (black) and undisrupted (red) regimes, reporting both the point-wise posterior medians (solid lines) and the 68% equal-tailed point-wise posterior probability bands (shaded area and dotted lines). We show the IRFs from horizon $k = 0$ up to $k = 12$ (i.e., four quarters). The figure shows substantial differences in the responses of the variables to the contractionary monetary policy shock between the two regimes. In accordance with our theoretical results, the GDP deflator and import price are more responsive, while the output and unemployment are less responsive in the regime of supply chain disruptions. The differences in the responses are statistically significant.

Appendix H shows that our results hold across several variations to the benchmark model: (i) different lag structures, (ii) a looser prior (i.e., $\lambda = 0.5$ instead of 0.25; see Appendix G.1

37. Except for the Federal Funds Rate, all the series are seasonally adjusted. Real GDP, GDP deflator, and import price enter the TVAR in log percent, whereas the Federal Funds Rate, unemployment, and ACR enter the TVAR in percent.

38. Restriction 4 enriches Restriction 1, which is intended for the identification of an adverse shock to aggregate demand, with the positive response of the Federal Funds Rate on impact.

39. To implement the sign and zero restrictions on IRFs, we use the penalty function approach (PFA) developed in Uhlig (2005) and Mountford and Uhlig (2009). The PFA consists of using a loss function to find an orthogonal matrix that satisfies the zero restrictions and that satisfies or comes close to satisfying the sign restrictions. Appendix G.2 provides the details on the PFA.

40. Appendix G.3 plots the posterior distribution of the threshold $\overline{ACR}$, together with the time series of the identified regimes using the median of the posterior $\overline{ACR}$.

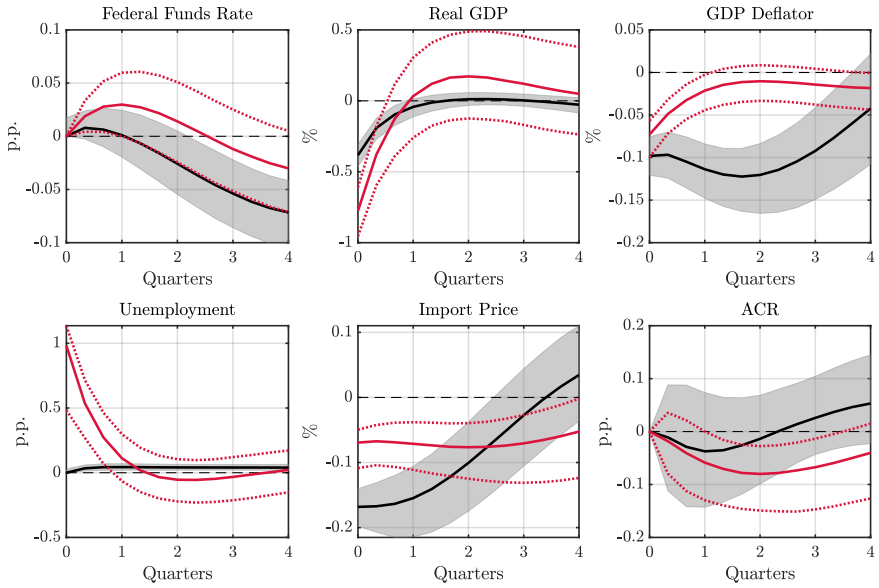



**Figure 16:** State-Dependent Effects of a Contractionary Monetary Policy Shock: Empirical Validation

*Notes.* The figure shows the IRFs to a one standard deviation contractionary monetary policy shock identified using Restriction 4 for both the supply chain disrupted and undisrupted regimes. The black solid (red solid) line shows the point-wise posterior medians, and the black shaded area (red dotted lines) depicts the 68% equal-tailed point-wise posterior probability bands for the supply chain disrupted (undisrupted) regime. The figure is based on 10,000 independent draws from the posterior.

for the details on the tightness of the prior), and (iii) longer horizons for the sign restrictions (i.e., $k = 1$ to $k = 1, 2, 3$). Appendix I shows that our results continue to hold when we use local projections with interaction terms, as in Ramey and Zubairy (2018) and Ghassibe and Zanetti (2022), to estimate the state-dependent effects of a contractionary monetary policy shock.

# 6. Conclusion

Our study presents the first index of global supply chain disruptions constructed from the Automatic Identification System, the mandatory tracking system installed on containerships serving major ports worldwide and made publicly available since 2017. To quantify the disruptions to the supply chain, we estimate the congestion in major ports around the world by developing a novel spatial clustering algorithm that tracks the vessels' positions and speeds in berth and anchorage areas within ports.

We develop a novel theoretical framework to examine supply chain disruptions within the context of imbalances between the supply and demand for goods that induce changes in prices and spare capacity. Our framework demonstrates that disturbances to the supply chain reduce output and inflate prices, as in standard models, but also lead to an increase in the economy's spare capacity. The co-movements of spare capacity, price, and output allow us to uniquely identify the supply chain shocks and explore their causal effects on macroeconomic outcomes through an SVAR model with sign and zero restrictions. Our model finds that supply chain shocks exert an immediate, large, and negative effect on real GDP and unemployment, while simultaneously causing a sharp rise in inflation.

We use the model to study changes in the effectiveness of monetary policy consequent to supply chain disruptions. We show both theoretically and empirically that monetary policy exerts a more substantial impact on inflation, albeit with diminished effectiveness on output, during periods of supply chain disruptions. Therefore, disruptions to the supply chain enhance the effectiveness of contractionary monetary policy in controlling inflation while mitigating its adverse effect on output.

Our study opens several valuable avenues for future research. First, our new index reveals significant heterogeneity in the congestion of ports around the world. It would be interesting to study whether the spillovers between ports are primarily driven by geographical proximity or production synergies and to investigate the redistribution of resources across ports in different locations consequent to the supply chain disruptions. Second, while our theoretical framework is based on single importer-exporter relationships to study the role of spare capacity, it would be worthwhile to extend the analysis to input-output networks and explore the role of spare capacity in the transmission of supply chain disruptions across firms in the network.The structure of the networks could potentially magnify or dampen the disturbances to the supply chain, which may trigger changes in the network's structure. Third, with the incorporation of predictive analytics, our spatial clustering algorithm could be fine-tuned to anticipate supply chain disruptions by identifying and analyzing subtle changes in the positions and speeds of containerships, as recorded in the AIS data. By effectively modeling these seemingly imperceptible changes, the algorithm could serve as a valuable tool for preemptive policy actions, enabling timely interventions to counter potential

disruptions before they materialize. We plan to pursue some of these extensions in future work.

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# Online Appendices

## A. A Density-Based Spatial Clustering Algorithm

In this appendix, we provide the technical details of our density-based spatial clustering algorithm, i.e., an iterative, multi-attribute, density-based spatial clustering of applications with noise (IMA-DBSCAN). Such an algorithm is applied in estimating port congestion for major container ports worldwide.[1] In the following sections, we first discuss the methodology embedded in our algorithm, followed by an illustrative case in which we apply the algorithm to the Port of Ningbo-Zhoushan in China to showcase its ability to identify anchorage and berth areas of a port while other methods cannot.

### A.1. Methodology

As shown in Figure A.1, the proposed IMA-DBSCAN has several distinct features, the most prominent of which is that it is comprised of two levels and is iterative in nature. On the first level, we derive the trajectory of each containership at each port under consideration from the AIS data. For each ship, a traditional DBSCAN (Ester et al. 1996) is employed to remove noise and cluster all its mooring points. As such, the first level can identify mooring areas, but is insufficient to distinguish between anchorage and berth areas of a port. The second level is then developed for this very purpose, where a spatial-temporal-DBSCAN (ST-DBSCAN; see Birant and Kut (2007)) is applied to the clustering. In the process, an iterative approach is undertaken to pin down a generalized and suitable parameter setting for the clustering algorithm. Another unique feature of the IMA-DBSCAN is the inclusion of multiple attributes at the second level. In addition to spatial information (e.g., coordinates), we also incorporate non-spatial information (e.g., headings and timestamps) to further improve the accuracy of clustering. In the following sections, we discuss the details specific to each level in the IMA-DBSCAN.

1. See https://www.worldshipping.org/top-50-ports (Accessed June 15, 2022) for the full list of ports. The Port of Tokyo Ko, Japan, is not included as its observations are merged with those of the Port of Keihin, Japan.

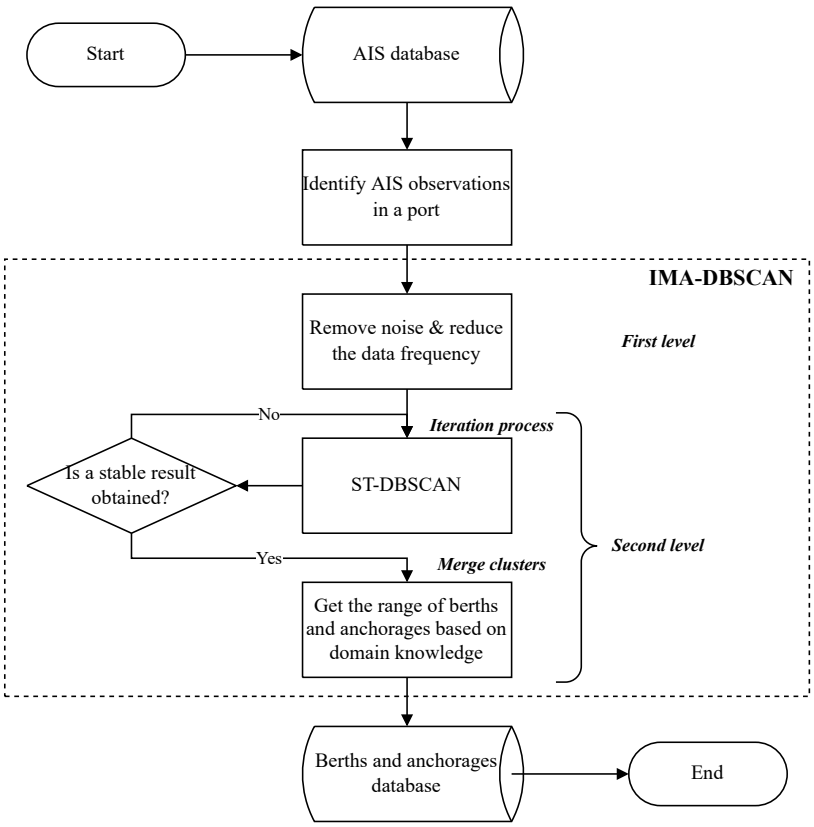



**Figure A.1:** Methodology Framework of the IMA-DBSCAN

### A.1.1. The First Level – Data Pre-Processing

While the AIS data contain highly detailed information on the positions of each ship, if we were to cluster these positions directly so as to determine the anchorage and berth areas of a port, several issues would arise. First, even if we could potentially restrict the underlying data to a single port area within a specific timeframe, there would still be a significant number of records so that inputting them directly into the DBSCAN would result in a lengthy processing time. Second, if the incidence of wrong assignments of the AIS signals were high, it would inevitably give rise to inaccurate clustering results, e.g., the identification of a cluster that is not a berth in reality, or that of a cluster which has an uncommonly large geographical area. Third, if a ship remained in a port area for too long (e.g., under maintenance), its positions recorded in the AIS data would be dense, causing the DBSCAN to incorrectly identify them as a cluster. Considering these issues, we must pre-process the AIS data before using them to identify the anchorage and berth areas of a port.

On the first level of the IMA-DBSCAN, we first filter the AIS data of each ship in the port area that record a speed of less than one knot. These positions indicate that a ship is either at a berth, at an anchorage, or in an unusual situation (e.g., under maintenance). We then compute the number of these positions; if the number exceeds an admissible range (e.g., less than 100 or more than 100,000), we consider the ship's data to be abnormal and make no further estimates for it. Next, a ship may call at a port repeatedly, so we set a certain period $\Delta t$ (e.g., 12 hours) as the cut-off period between two consecutive arrivals. If the time between the two arrivals is more than $\Delta t$, they are included as two separate port calls. Furthermore, in order to reduce the frequency of the data while ensuring uniformity, we only keep the first data point for each hour. Lastly, for each port call of a ship, its positions are clustered by the traditional DBSCAN with parameters $Eps$ and $MinPts$. We set a value for $Eps$ that is small enough so that those mooring areas of the ship are identified, as well as an appropriate value for $MinPts$ to ensure that brief stops are recognized as noise. Up to now, the pre-processing of the AIS data is complete, and the resulting samples are consolidated and applied in the identification of anchorage and berth areas of a port on the second level of the IMA-DBSCAN. For reference, the pseudo-code for the first level of the IMA-DBSCAN can be found in Algorithm 1.

### A.1.2. The Second Level – Multiple Attributes and Iteration

*Information on Headings*. As mentioned in the main text, the AIS data encompass both spatial (e.g., coordinates) and non-spatial (e.g., headings and timestamps) information. In Figure 1 in the main text, we plot the positions of a ship in a port as well as their headings; we find that, while the headings of a ship in a berth are either in the same direction or exactly opposite, those in an anchorage area are random and no discernible pattern can be observed. Such an observation is consistent with what we see in reality, as it is difficult for a ship to maintain the same heading in an anchorage area due to drastic changes in wind and waves.

Therefore, on the second level of the IMA-DBSCAN, we take advantage of such information on headings to achieve a more accurate estimation.[2] Specifically, we set up three

2. Such non-spatial information is also useful when we distinguish between different berths (see Algorithm

parameters in the IMA-DBSCAN instead of the usual two in the traditional DBSCAN, i.e., $Eps1$, $Eps2$, and $MinPts$, where $Eps1$ is the maximum geographical coordinate (spatial) distance, $Eps2$ is the maximum non-spatial distance between two headings, and $MinPts$ is the minimum number of points within the distance of $Eps1$ and $Eps2$. The geographical coordinate (spatial) distance $D$ is calculated using the Haversine formula:

$$D\Big[(x_1, x_2), (y_1, y_2)\Big] = 2 \cdot R \cdot \arcsin\left[\sqrt{\sin^2\left(\frac{x_1 - y_1}{2}\right) + \cos x_1 \cos y_1 \sin^2\left(\frac{x_2 - y_2}{2}\right)}\right], \quad \text{(A.1)}$$

where the coordinates are measured in radians, and $R = 6,371$ is the mean radius of Earth in kilometers. On the other hand, the non-spatial distance $\Delta h$ is calculated as:

$$\Delta h(h_1, h_2) = \begin{cases} |h_1 - h_2|\,, & \text{if } |h_1 - h_2| \leq 180°; \\ 360° - |h_1 - h_2|\,, & \text{otherwise.} \end{cases} \quad \text{(A.2)}$$

With the two measures of distance defined above, the neighbors of a point are those with geographical coordinate (spatial) distance less than $Eps1$ and non-spatial distance less than $Eps2$, and a core is defined as a point with more than or equivalent to $MinPts$ neighbors. The clusters in the IMA-DBSCAN contain only these cores.

*Iteration Process*. As discussed previously, there are three parameters to be set in the IMA-DBSCAN. Since the geographical shapes of anchorage and berth areas differ significantly across ports, the values of the three parameters should vary in principle so as to achieve better estimation results. Therefore, we propose an iterative method to obtain these parameter values. In particular, while $Eps2$ is fixed at 1°, our method allows the values of $Eps1$ and $MinPts$ to vary between different ports. Specifically, in the process of iteration, we define four intermediate variables, i.e., $Dist$, $m$, $m'$, and $NumC$. $Dist$ is defined as the average distance between a point in a cluster and the center of the cluster to which it belongs. $m$ denotes the number of points, while $m'$ denotes the number of noisy points (which is set to zero at initialization). Lastly, $NumC$ denotes the number of clusters.[3] Given these

2). In our initial experiment, the coordinates could only help us identify the approximate locations of anchorage and berth areas of a port, not to mention the exact number of berths.

3. Since there are no clusters at initialization, we treat all points as if they were in the same cluster. In addition, if all points are noisy, we set $NumC = 1$.

intermediate variables, $MinPts$ and $Eps1$ are calculated as:

$$Eps1 = \alpha \cdot Dist,$$
$$MinPts = \beta \cdot \frac{m - m'}{NumC}.$$

In terms of $\alpha$ and $\beta$, although there are no explicit restrictions on their values, they should lie within a reasonable range so as to ensure both the convergence of the algorithm and the validity of the identification results. After examining the performance of the IMA-DBSCAN under various parameters settings, we find that an admissible range of ($0.4 \leq \alpha \leq 0.6$, $0.06 \leq \beta \leq 0.1$) is appropriate. We also define an intermediate variable $Dist_0$, which is used to record the value of $Dist$ in the previous iteration. It is set to zero at initialization.

Subsequently, we run the ST-DBSCAN iteratively. At each iteration, an ST-DBSCAN is performed with $Eps1$ and $MinPts$ set to their contemporaneous values and $Eps2$ set to 1°. Its outputs are such that each point is either assigned to a cluster or classified as noise. Accordingly, the values of the intermediate variables are updated, as well as those associated with $Eps1$ and $MinPts$. Such values are then re-applied in the ST-DBSCAN for the next iteration. The whole process will stop when $Dist - Dist_0$ is less than or equal to $\Delta Dist$ (e.g., 100 m), and as a result, each point is either assigned to a cluster or classified as noise. We then treat the areas of the clusters as berths and those of noisy points as anchorages.

*Information on Timestamp*. After running the ST-DBSCAN, we find that there exist a large proportion of clusters that should be merged together as they essentially represent the same berth in reality. To achieve a more accurate identification of berth areas, we merge certain clusters by taking advantage of the time information (i.e., timestamps) in the AIS data (see Figure A.2 for an illustration). More precisely, we first calculate the start and end times of each port call in each cluster. Subsequently, since only one ship can dock at a berth for a given moment, for each cluster under consideration, we find the cluster that is the closest to it, and then check whether there is any overlap in the docking times. If there exists (at least) one overlap, the two clusters are considered to represent two different berths. If there is no overlap, the two clusters are merged together to represent one berth.

Furthermore, in order to differentiate between different anchorage areas, we perform

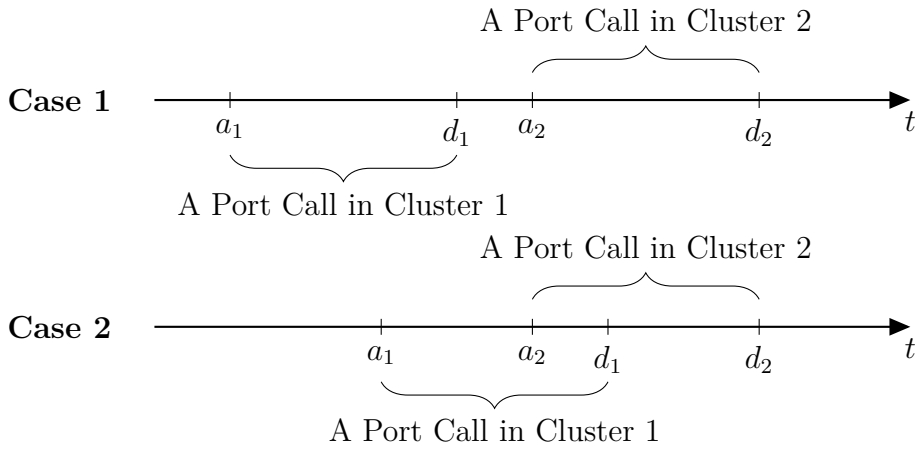



**Figure A.2:** Merging Clusters

*Notes.* The figure presents two cases and discusses when to merge clusters after running the ST-DBSCAN on the second level. $a_1$ and $d_1$ denote the arrival and departure times of a ship in a port call that is assigned to cluster 1, while $a_2$ and $d_2$ denote those associated with a port call that is assigned to cluster 2, which is the closest to cluster 1 in geographical distance. In the first case, since there is no overlap in the docking times, clusters 1 and 2 are merged. In the second case, since there is an overlap, the two clusters are kept separate as the two ships cannot dock at a single berth at the same time.

another DBSCAN on those points that are classified as noise. In the process, the two parameters associated with the DBSCAN, i.e, $Eps'$ and $MinPts'$, are set according to our domain knowledge. Finally, we remove clusters with less than $N$ port calls, with $N$ set according to our domain knowledge. For reference, the pseudo-codes for the second level of the IMA-DBSCAN can be found in Algorithms 2, 3, and 4.

Lastly, in the estimation of port congestion for the major container ports worldwide, the following parameter values are set for the IMA-DBSCAN: for the first level, we have $\Delta t = 12$ hours, $Eps = 50$ m, and $MinPts = 10$; for the second level, we have $\alpha = 0.5$, $\beta = 0.08$, $\Delta Dist = 100$ m, $Eps' = 1000$ m, $MinPts' = 50$, and $N = 5$.

**Algorithm 1** Level 1 IMA-DBSCAN

**Inputs:**

$A_l = \{a_{1,l}, \ldots, a_{n,l}\}$: the set of coordinates recorded in the AIS data for a ship $l$
$S_l = \{s_{1,l}, \ldots, s_{n,l}\}$: the set of speeds recorded in the AIS data for a ship $l$
$T_l = \{t_{1,l}, \ldots, t_{n,l}\}$: the set of timestamps recorded in the AIS data for a ship $l$

**Outputs:**

$D_l = \{d_{1,l}, \ldots, d_{m,l}\}$: the coordinates of the first observation for each hour in $B_l$
$H_l = \{h_{1,l}, \ldots, h_{m,l}\}$: the headings of the first observation for each hour in $B_l$

*/* Data Pre-Processing */*
$B_l = \{b_{1,l} \ldots b_{k,l}\} \leftarrow$ the set of coordinates in $A_l$ that indicate a speed less than 1 knot
*/* Exception Identification */*
**if** $|B_l| < 100$ **or** $|B_l| > 100,000$ **then**
    Remove the data and stop ▷ *The ship has an abnormal port call*
**else**
    Continue
**end if**
*/* DBSCAN Clustering */*
$X \leftarrow b_{1,l}$
**for** $i \leftarrow 2 : k$ **do**
    **if** $t_i - t_{i-1} \leq \Delta t$ **then**
        Append $b_{i,l}$ to $X$
    **else**
        $DBSCAN(X, Eps, MinPts)$
        $X \leftarrow \emptyset$
        Append $b_{i,l}$ to $X$
    **end if**
**end for**
Remove the observations labeled as noise from $B_l$
Keep only the first observation for each hour in $B_l$ ▷ *Note that only $m$ observations remain in $B_l$ at this stage*
$D_l = \{d_{1,l}, \ldots, d_{m,l}\} \leftarrow$ the coordinates of the first observation for each hour in $B_l$
$H_l = \{h_{1,l}, \ldots, h_{m,l}\} \leftarrow$ the headings of the first observation for each hour in $B_l$

**Algorithm 2** Level 2 IMA-DBSCAN

**Inputs:**

$\boldsymbol{D} = \{D_1, \ldots, D_L\}$: the set of coordinates for all ships after Level 1 IMA-DBSCAN
$\boldsymbol{H} = \{H_1, \ldots, H_L\}$: the set of headings for all ships after Level 1 IMA-DBSCAN
$\boldsymbol{O} = \{\boldsymbol{D}, \boldsymbol{H}\} = \{o_1, \ldots, o_M\}$: the combined set of coordinates and headings

**Outputs:**

$C_{berth}$: the set of clusters marked as berths
$C_{anchorage}$: the set of clusters marked as anchorages

*/* Parameter Initialization */*
$Dist \leftarrow$ the average distance between a point in $\boldsymbol{D}$ and the center of the mass of $\boldsymbol{D}$
$m \leftarrow |\boldsymbol{D}|$
$Eps1 \leftarrow \alpha \cdot Dist$
$MinPts \leftarrow \beta \cdot m$
*/* Iteration Process */*
$Dist_0 \leftarrow 0$
**while** $Dist - Dist_0 > \Delta Dist$ km **do**
    $ST - DBSCAN(\boldsymbol{O}, Eps1, Eps2 = 1°, MinPts)$ ▷ *See function ST-DBSCAN*
    $Dist_0 \leftarrow Dist$
    $Dist \leftarrow$ the average distance between a non-noisy point in $\boldsymbol{D}$ and the center of the mass of its assigned cluster
    $m' \leftarrow |$noisy points in $\boldsymbol{O}|$
    $NumC \leftarrow |$clusters in $\boldsymbol{O}|$
    $Eps1 \leftarrow \alpha \cdot Dist$
    $MinPts \leftarrow \beta \cdot (m - m') / NumC$
**end while**
*/* Merging Clusters */*
Use the center of the mass of each cluster to calculate the distance in between
**for all** clusters $c$ in $\boldsymbol{O}$ **do**
    $c' \leftarrow$ the nearest cluster less than 500 m away from $c$
    **if** the docking times of $c'$ and $c$ do not overlap **then**
        Replace the cluster label of $c'$ with that of $c$
    **end if**
**end for**
*/* Berth and Anchorage Detection */*
$C_{berth} \leftarrow$ clusters in $\boldsymbol{O}$
$C_{anchorage} \leftarrow DBSCAN($Noisy points in $\boldsymbol{O}, Eps', MinPts')$
*/* Exception Removal */*
**for all** clusters $c$ **in** $C_{berth}$ **and** $C_{anchorage}$ **do**
    $NumP \leftarrow$ the number of port calls in cluster $c$
    **if** $NumP < N$ **then**
        Remove $c$
    **end if**
**end for**

**Algorithm 3** ST-DBSCAN

**Inputs:**

$\boldsymbol{O} = \{o_1, \ldots, o_M\}$: the combined set of coordinates and headings
$Eps1$: maximum geographical coordinate (spatial) distance
$Eps2$: maximum non-spatial distance
$MinPts$: minimum number of points within the distance of $Eps1$ and $Eps2$

**Outputs:**

$C = \{c_1, \ldots, c_M\}$: the set of clusters in $\boldsymbol{O}$

```
/* The codes are adapted from those in Birant and Kut (2007).                    */
function ST − DBSCAN(D, Eps1, Eps2, MinPts)
    ClusterLabel = 0
    for i ← 1 : m do
        if o_i is not in a cluster then
            Y ← RetrieveNeighbors(o_i, Eps1, Eps2)    ▷ See function RetrieveNeighbors
            if |Y| < MinPts then
                Mark o_i as noise
            else                                                ▷ Construct a new cluster
                ClusterLabel ← ClusterLabel + 1
                for j ← 1 : |Y| do
                    Mark all objects in Y with current ClusterLabel
                end for
                Push(all objects in Y)
                while not IsEmpty() do
                    CurrentObj = Pop()
                    Z ← RetrieveNeighbors(CurrentObj, Eps1, Eps2)
                    if |Z| ≥ MinPts then
                        for all objects o in Z do
                            if o is not marked as noise or it is not in a cluster then
                                Mark o with current ClusterLabel
                                Push(o)
                            end if
                        end for
                    end if
                end while
            end if
        end if
    end for
    C = {c_1, ..., c_M} ← the set of clusters in O
end function
```

**Algorithm 4** RetrieveNeighbors

**Inputs:**

$o$: an observation in $\boldsymbol{O}$
$Eps1$: maximum geographical coordinate (spatial) distance
$Eps2$: maximum non-spatial distance

**Outputs:**

$Neighbors$: the set of neighbors for $o$

**function** $RetrieveNeighbors(o, Eps1, Eps2)$
  $Neighbors \leftarrow \emptyset$
  **for all** observations $o'$ **in** $O$ **do**
    $Dist1 \leftarrow D(o, o')$ ▷ *See Equation* (A.1)
    $Dist2 \leftarrow \Delta h(o, o')$ ▷ *See Equation* (A.2)
    **if** $Dist1 \leq Eps1$ **and** $Dist2 \leq Eps2$ **then**
      Append $o'$ to $Neighbors$
    **end if**
  **end for**
  **return** $Neighbors$
**end function**

## A.2. Illustrative Case: Port of Ningbo-Zhoushan

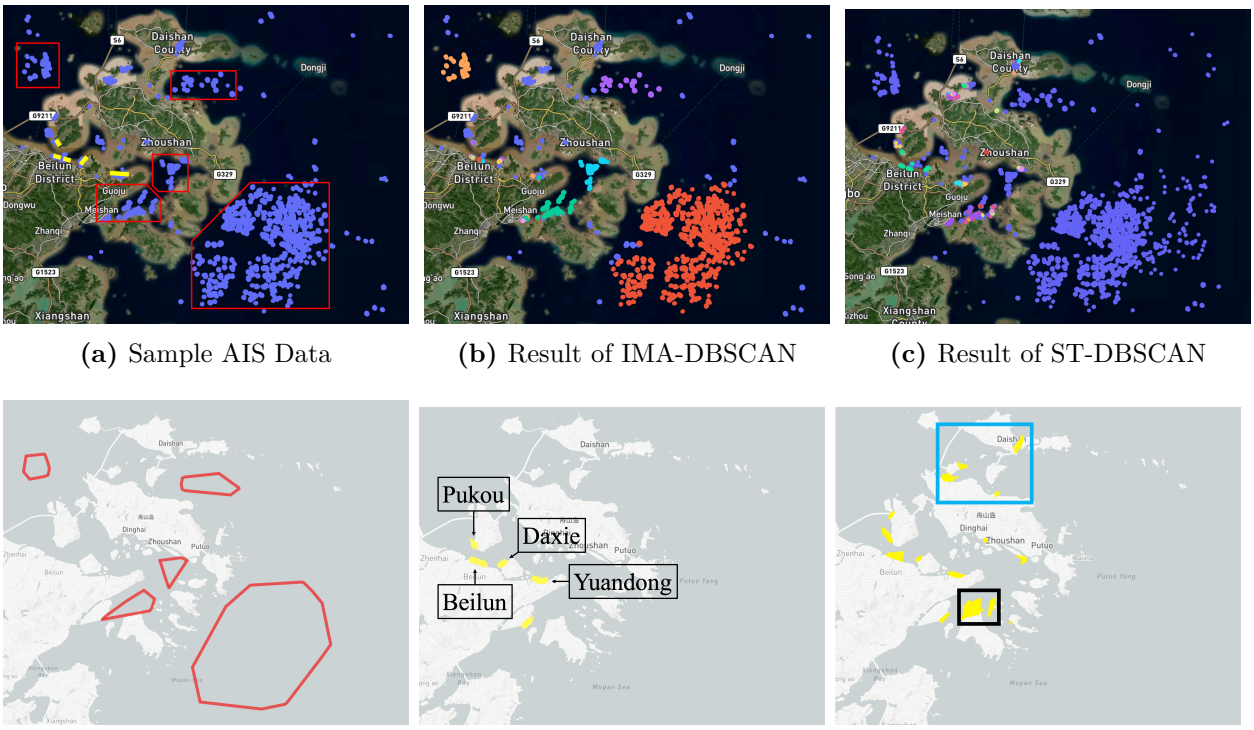
To illustrate the ability of IMA-DBSCAN to accurately identify anchorage and berth areas of a port while other methods cannot, we apply the algorithm to the Port of Ningbo-Zhoushan in China. We consider such a specific example mainly because of its complex port layout. Figure A.3a displays 50,000 AIS observations taken in January 2020 within the Port of Ningbo-Zhoushan.[4] The observations are denoted by blue dots on the map, with each dot signifying the position of a low-speed containership. Prior to applying IMA-DBSCAN to the AIS data, by utilizing both satellite images and nautical charts, we mark the approximate locations of anchorages and berths in distinct colors. The red boxes denote the anchorage areas, and the yellow highlights represent the berth locations.

Figure A.3b presents the clustering outcomes of IMA-DBSCAN for the Port of Ningbo-Zhoushan, replicating the map in Figure A.3a to enable a direct comparison between our

4. This example focuses on a one-month time snapshot. It is plausible to presume that the identification results will be indicative of berth and anchorage areas in subsequent months, as we anticipate no significant short-term changes in the port areas. When implementing IMA-DBSCAN in real-world scenarios, periodic identification can be conducted to monitor potential alterations in port anchorages and berths.

algorithm's results and the actual observations. Evidently, the blue-marked outliers do not belong to any anchorage or berth, indicating that ships anchored in this region only for a brief period. In addition, the clusters in Figure A.3b (printed in purple, green, orange, blue, and yellow respectively) correspond to the anchorages in Figure A.3a (represented by red polygons). For a better illustration, we also depict the convex hulls generated by these clusters in Figure A.3d. Furthermore, in Figure A.3e, we highlight the locations of four terminals within Ningbo-Zhoushan, i.e., Pukou, Daxie, Beilun, and Yuandong. By consulting satellite maps, we confirm the accuracy of such identification results, as each terminal berth is precisely identified, and the recognized areas closely resemble reality.

To assess the performance of IMA-DBSCAN, we compare it to that obtained from ST-DBSCAN, as ST-DBSCAN can handle spatial-temporal databases and is considered one of the most popular spatial clustering algorithms in literature. Figure A.3c depicts the results from ST-DBSCAN, clearly showing that it produces less accurate outcomes than IMA-DBSCAN. To be more specific, ST-DBSCAN can generally identify points within the anchorages (marked in blue in A.3c); however, it incorrectly identifies several high-density areas as berths that are not, in reality, actual berths. For instance, in the blue rectangle in Figure A.3f, points that should be considered noise are identified as berths since ships remain at these locations for extended periods (potentially for maintenance). Additionally, within the black rectangle, ST-DBSCAN misidentifies several points as berths that should be categorized as mooring areas. Therefore, while applying ST-DBSCAN to the sample data offers some insight into the arrangement of anchorages, it fails to provide an accurate identification of berth locations.




**(a)** Sample AIS Data **(b)** Result of IMA-DBSCAN **(c)** Result of ST-DBSCAN

**(d)** Anchorages (IMA-DBSCAN) **(e)** Berths (IMA-DBSCAN) **(f)** Berths (ST-DBSCAN)

**Figure A.3:** Identification of Anchorage and Berth Areas in the Port of Ningbo-Zhoushan

*Notes.* In Figure (a), the sample data comprises 50,000 AIS observations taken in January 2020 within the Port of Ningbo-Zhoushan. The observations are denoted by blue dots on the map and correspond to coordinates ranging from 121.60°E to 123.00°E and from 29.50°N to 30.35°N. With the help of satellite maps and nautical charts, we have identified the approximate areas of the anchorages using red polygons and the approximate locations of the berths using yellow rectangles. Two clustering algorithms, IMA-DBSCAN and ST-DBSCAN, have been applied to the sample data, and the resulting clusters are illustrated in Figures (b) and (c) respectively. It should be noted that blue dots in Figures (b) and (c) indicate noise. In Figure (d), the anchorages from Figure (b) are plotted separately and marked in red, while in Figure (e), the berths from Figure (b) are plotted separately and marked in yellow. The four terminals are identified as Pukou, Daxie, Beilun, and Yuandong. Finally, in Figure (f), the yellow areas represent the approximate positions of the berths as identified by the ST-DBSCAN, while the blue and black rectangles indicate misidentifications of noise as berths and confusion between anchorages and berths respectively.

# B. Discussion on the Shortcomings of Existing Indices of Supply Chain Disruptions

In this appendix, we elaborate on the shortcomings of using the shipping cost, the sub-components of the manufacturing PMI, and other indices of supply chain disruptions in the causality assessment.

Since our goal is to identify a supply chain disruption shock, the variables to include in the SVARs should in principle reflect how well the global supply chain is functioning. Shipping cost is a natural candidate, as supply chain issues could arise internationally due to a shortage of containers and port congestion (Klachkin 2021; Benigno et al. 2022). However, it should be noted that dynamics in the transportation sector are subject to both supply- and demand-side factors. An increase in the demand for tradable goods would fuel the derived demand for international shipping services, leading to a tighter transportation market and a higher shipping cost.

Another choice is the sub-components of the manufacturing PMI, such as "delivery times", which are used in Kamali and Wang (2021) and Benigno et al. (2022) to capture the extent of supply chain delays and hence act as a barometer of the effectiveness of the global supply chain.[5] Yet, since the PMI is computed based on responses to survey questions, it is inevitably subject to large, persistent, and time-varying measurement errors. Moreover, the PMI does not differentiate whether an increase in delivery times is caused by a disruption to the supply chain or the actual production itself.

In addition to the shipping cost and PMI sub-components, the Kiel trade indicator (Stamer 2021), which uses the same AIS data as ours, provides another angle to assess the widespread strain on the global supply chain; not only does it estimate imports and exports, but it also tracks containership traffic at major ports as well as freight on stationary ships. However, it has several drawbacks. First, the calculation of twenty-foot equivalent units (TEU) is problematic because the draught of a containership is not indicative of its

5. For instance, IHS Markit (Williamson 2021) calculates the suppliers' delivery times using responses to its PMI business surveys. Specifically, participating purchasing managers are asked if it takes their suppliers more or less time to provide inputs to their factories on average. The percentages of companies reporting an improvement, deterioration, or no change in delivery times are then weighted to derive the index.

loading status since loading and unloading operations could occur simultaneously. Second, variations in imports and exports are also subject to demand-side factors, leading to endogeneity issues. Third, the calculation of cargo capacity tied up at ports does not differentiate mooring positions of containerships (berth vs. anchorage), which, as argued in Talley and Ng (2016), could result in an overestimation of port congestion.

Other indices of supply chain disruptions employ either more advanced techniques (e.g., machine learning) or more granular data (e.g., import transactions). Burriel et al. (2023) develop a text-based index of supply disruptions, in which they apply the methodology by Baker, Bloom, and Davis (2016) using newspaper data. While such an index overcomes the endogeneity issue by selecting only supply-side events, it is not immune to measurement errors that naturally arise from word definitions; for instance, a disruption to "supply" is not the same as one to the "supply chain", as the former may stem from a shortage in labor supply. Another example is Smirnyagin and Tsyvinski (2022), where they use the S&P Global Panjiva dataset, a comprehensive source of U.S. seaborne import records, to derive a measure of supply chain disruptions. They identify supply chain disruptions by monitoring regular and active consignee-shipper relationships over quarterly periods; a disruption occurs when a consistently active relationship goes inactive for a quarter and then resumes. While this identification isolates disruptions in the context of established trading relationships, potential endogeneity issues could still arise if, for instance, a consignee temporarily halts orders due to decreased demand, not because of a disruption in the supply chain. It might be challenging to disentangle these situations solely based on the activity status of consignee-shipper relationships.

# C. Discussion on the Assumptions in the Model

In this appendix, we discuss two critical assumptions in the model: matching frictions on the international product market and endogenous separation of exporter-importer matches on transportation cost. First, to represent the matching frictions in a tractable manner, we assume that the number of trades between exporters and importers are governed by a matching function. Second, to succinctly capture the decision-making process between an

exporter and an importer when their trade is subject to a transportation cost, we assume that upon meeting, both parties choose to endogenously separate from each other once the idiosyncratic transportation cost to pay lies above a reservation threshold. We discuss each of these two assumptions in turn.

## C.1. The Matching Function

There is ample literature that studies the origins of matching frictions on the international product market, including but not limited to locating and building connections with overseas buyers (Benguria 2021; Krolikowski and McCallum 2021; Lenoir, Martin, and Mejean 2022), costly information acquisition about market conditions elsewhere (Allen 2014; Chaney 2014), and informal trade barriers such as common language (Melitz and Toubal 2014) and geography (Eaton and Kortum 2002). Different as these theories/evidence might be, they all show that there exist prevalent trade barriers between exporting and importing firms, implying that not all the unmatched exporters engage in trade, while not all the sourcing visits by importers are successful. Following in this vein, we assume a constant-returns-to-scale matching function that summarizes how unmatched exporters and visits of importers are transformed into trades through the matching process. As such, we abstract away from modeling the complex matching process while still preserving its main implication: the unmatched exporters only engage in trade with probability $f(\theta)G(\tau) < 1$ and the visits of importers to exporters are only successful with probability $q(\theta)G(\tau) < 1$.

## C.2. Endogenous Separation on Transportation Cost

Much in the same way the separation margin on the labor market could be modeled endogenously when workers face productivity shocks to their employment matches and bad draws possibly lead to separations (Bils, Chang, and Kim 2011; Menzio and Shi 2011; Fujita and Ramey 2012), the separation margin on the international product market could be modeled endogenously when exporters face idiosyncratic transportation costs to their trading relationships with importers and bad draws possibly lead to terminations of such relationships. Such a modeling assumption is reasonable only if we find convincing evidence that (1) trans-

portation cost is taken into account when trading partners decide on a potential trade, and (2) there exists a threshold of transportation cost above which trading partners choose to sever their relationship.

The prediction that transportation cost affects the possibility of a trade has been examined empirically in the international trade literature. To name a few, evidence in Rodrigue (2020) underlines that across all modes, raising transportation costs by 10% reduces trade volumes by more than 20%. In the context of maritime transportation, Brancaccio, Kalouptsidi, and Papageorgiou (2020) exploit changes in tariffs across the trade network to estimate the elasticity of world trade value with respect to shipping costs. They estimate that a 1% change in shipping costs leads to approximately a 1% change in world trade value. Similarly, Wong (2022) estimates the containerized trade elasticity with respect to freight rates using the round-trip effect as an instrument (in particular, for route $i, j$, the author uses a Bartik-style instrument to proxy for the predicted trade value on route $j, i$). The author reports that a 1% increase in per unit container freight rates decreases containerized trade value by 2.8% when dyad-by-product controls are included in the regression. Together, these elasticities emphasize that transportation costs are indeed taken into account when trading partners choose to form a relationship, and that a rise in transportation cost deters international trade substantially.

Both theory and casual observation also suggest the presence of a reservation transportation cost, which trading partners often consider when assessing the profitability of a potential trade on the international product market. Notably, to reconcile the empirical evidence that export and import intensities vary across plants, Kasahara and Lapham (2013) extend the model in Melitz (2003) by allowing for heterogeneity in transportation costs. Incorporating heterogeneous transportation costs provides a plausible self-selection mechanism regarding trade decisions, as plants with low transportation costs self-select into exporting and importing. As such, there must exist a threshold value of transportation cost below which plants choose to engage in trade.[6] Casual observations are also consistent with this

6. A similar argument can be found in the discussion of transport infrastructure and its effects on firm's exporting decision. For instance, Naudé and Matthee (2011) argue that the availability of transport infrastructure will have a threshold effect – a certain minimum of transport infrastructure is required for a firm to start exporting, but once the threshold is reached, improved infrastructure will not necessarily have a large impact on the extent of an individual firm's exports. Since the availability of transport infrastructure

theoretical prediction. For instance, according to the Global Transport Costs Dataset for International Trade (UNCTAD 2021), the cost of transporting medical care commodities by sea from China to the U.S. normally accounts for 5% of their Free On Board values. When the transportation cost rises above 5%, exporters in China will reconsider whether it is still profitable to export medical care commodities to the U.S. Hence, following the Covid-19 pandemic, as the transportation cost skyrocketed while the initial increase in the final price of medical care commodities was not on par, trades collapsed as exporters in China exited the market, leading to a great shortage of medical supplies in the U.S. Furthermore, it is noted that the reservation transportation cost is largely fixed in the short run, given that transportation technology and price outlook for shipping fuel are unlikely to vary in few years' time. As such, our modeling assumption regarding the flexible-price aggregate supply is consistent with the reality.

Lastly, the modeling assumption that transportation cost follows a log-normal distribution is borrowed from Kasahara and Lapham (2013). We make this crude but convenient assumption for two reasons. First, since transportation cost varies across countries, routes, directions, and commodities in reality (Brown, Englert, and Hoffmann 2021), an assumption that it is randomly distributed according to a distribution is more plausible than a fixed value (for instance, the "iceberg" formulation of trade costs as in Samuelson (1954)). Second, using a log-normally distributed transportation cost provides us with a purely exogenous measure of transportation cost. With the scale parameter of the log-normal distribution of transportation costs acting as the model counterpart to the ACR, our model mimics the positive relationship between the ACR and shipping costs, as shown in Figure 5a in the main text.[7]

(at least partially) determines the transportation cost, this argument is consistent with the presence of a reservation transportation cost that firms take into account when making an exporting decision.

7. Alternatively, we could augment the current model with a full-fledged transportation sector in which the interactions between exporters and shipowners determine the transportation cost. Such an endogenous setting can be found in Brancaccio, Kalouptsidi, and Papageorgiou (2020) and Bai and Li (2022). Nonetheless, we maintain the current setting for its tractability.

# D. Long Proofs

## D.1. Proof of Proposition 1

We first derive Equation (14). Rewriting Equations (12) and (13) and applying the property $\theta = f(\theta)/q(\theta)$, we obtain that:

$$\theta(p, \bar{z}) = \frac{1-\eta}{\eta\rho}\big(p - \bar{z} + \beta \mathbb{E}_{z'} S(z')\big). \tag{D.1}$$

Then we rewrite $\mathbb{E}_{z'} S(z')$. Using the definition of $S(z)$, we have:

$$S(z) = p - z + \big(1 - \eta f(\theta)\big)\beta \mathbb{E}_{z'} S(z').$$

Subtracting Equation (12) from the above equation yields $S(z) = \bar{z} - z$. Replacing $S(z')$ in $\mathbb{E}_{z'} S(z')$ with $\bar{z} - z'$, we derive that:

$$\begin{aligned}
\mathbb{E}_{z'} S(z') &= \int_0^{\bar{z}} (\bar{z} - z') dG(z') \\
&= (\bar{z} - z') G(z') \Big|_0^{\bar{z}} + \int_0^{\bar{z}} G(z') dz' \\
&= \int_0^{\bar{z}} G(z') dz'.
\end{aligned}$$

Subsequently, replacing $\mathbb{E}_{z'} S(z')$ in Equation (D.1) with $\int_0^{\bar{z}} G(z') dz'$ gives Equation (14).

The first property is obvious. Since $\theta$ cannot be negative, for a given $\bar{z}$, $p$ is bounded on $[p^{min}, +\infty)$, where $p^{min}$ is such that it solves $p^{min} - \bar{z} + \beta \int_0^{\bar{z}} G(z') dz' = 0$ for any $\bar{z} > 0$. As for the second and third properties, we derive that:

$$\frac{\partial \theta(p, \bar{z})}{\partial p} = \frac{1-\eta}{\eta\rho} > 0.$$

Hence, the product market tightness $\theta(p, \bar{z})$ is strictly increasing and linear on $[p^{min}, +\infty)$.

The fourth property is also obvious from the definition of $\bar{z}^{max}$, as $\theta$ cannot be negative. In terms of the fifth and last properties, we derive that:

$$\frac{\partial \theta(p, \bar{z})}{\partial \bar{z}} = \frac{1-\eta}{\eta\rho}\big(-1 + \beta G(\bar{z})\big) < 0,$$

$$\frac{\partial^2\theta(p,\bar{z})}{\partial\bar{z}^2} = \frac{(1-\eta)\beta}{\eta\rho}\frac{1}{\bar{z}\sigma}\phi(\frac{\log\bar{z}-\gamma}{\sigma}) > 0,$$

where $\phi(.)$ is the standard normal probability density function. Hence, the product market tightness $\theta(p,\bar{z})$ is strictly decreasing and convex on $(0,\bar{z}^{max}]$.

## D.2. Proof of Proposition 2

The first property is obvious. When $p = p^{min}$, $\theta(p^{min}) = 0$, $f\big(\theta(p^{min})\big) = 0$, and $c_s^{flex}(p^{min}) = 0$. When $p \to +\infty$, $\lim_{p\to+\infty}\theta(p) = +\infty$, $\lim_{p\to+\infty} f\big(\theta(p)\big) = 1$, and hence $\lim_{p\to+\infty} c_s^{flex}(p) = G(\tau)l$. In terms of the second and third properties, we derive that:

$$\frac{dc_s^{flex}(p)}{dp} = \frac{1-\eta}{\eta\rho}\frac{\big(1-G(\tau)\big)q(\theta)^{1+\xi}G(\tau)l}{\big(1-G(\tau)+f(\theta)G(\tau)\big)^2} > 0,$$

$$\begin{aligned}\frac{d^2c_s^{flex}(p)}{dp^2} =& -\Big(\frac{1-\eta}{\eta\rho}\Big)^2\big(1-G(\tau)\big)G(\tau)l \\ &\cdot\frac{\big(1-G(\tau)+f(\theta)G(\tau)\big)\theta^{\xi-1}(1+\xi)(1+\theta^{\xi})^{-\frac{1+\xi}{\xi}-1}+2G(\tau)q(\theta)^{2(1+\xi)}}{\big(1-G(\tau)+f(\theta)G(\tau)\big)^3} < 0.\end{aligned}$$

Hence, the flexible-price aggregate supply $c_s^{flex}$ is strictly increasing and concave on $[p^{min},+\infty)$.

## D.3. Proof of Proposition 4

Since we look for a flexible-price equilibrium with positive consumption, we restrict our search of price $p$ within the range $[p^{min},+\infty)$. The equilibrium condition (21) can be re-written as:

$$\frac{f\big(\theta(p)\big)p}{1-G(\tau)+f\big(\theta(p)\big)G(\tau)} = \frac{\chi^{\epsilon}}{1+\chi^{\epsilon}}\frac{\mu}{G(\tau)l}. \tag{D.2}$$

For any $\tau > 0$, the right hand side is a constant that is strictly positive. For the left hand side, when $p = p^{min}$, $\theta(p^{min}) = 0$, and $f\big(\theta(p^{min})\big) = 0$, it has a limit of zero; when $p \to +\infty$, $\lim_{p\to+\infty}\theta(p) = +\infty$, and $\lim_{p\to+\infty} f\big(\theta(p)\big) = 1$, it has a limit of positive infinity. For $p \in [p^{min},+\infty)$, the derivative of the left hand side with respect to $p$ is given by:

$$\frac{d}{dp}\Big[\frac{f\big(\theta(p)\big)p}{1-G(\tau)+f\big(\theta(p)\big)G(\tau)}\Big] = \frac{\big(1-G(\tau)\big)\frac{1-\eta}{\eta\rho}q(\theta)^{1+\xi}p + f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)}{\big(1-G(\tau)+f(\theta)G(\tau)\big)^2} > 0.$$

Therefore, the left hand side is strictly increasing from zero to positive infinity on $[p^{min}, +\infty)$. As such, there is a unique $p \in [p^{min}, +\infty)$ that solves Equation (D.2).

## D.4. Proof of Proposition 5

We first consider an adverse shock to aggregate demand. No matter whether the negative aggregate demand shock is represented by a decrease in money supply $\mu$ or in the taste for consumption of goods $\chi$, the right hand side of Equation (D.2) will decrease. To balance both sides of Equation (D.2), price $p$ will decrease, since the derivative of the left hand side with respect to $p$ is positive (see the proof for Proposition 4). As $p$ decreases, by the second property in Proposition 1 and the second property in Proposition 2, product market tightness $\theta$ and consumption (or equivalently, output) $c$ will decrease. Since both $p$ and $\theta$ decrease, according to Equation (10), import price $r$ will decline as well. For the matching cost, $G(\tau)l-c$, and spare capacity (or equivalently, unemployment), $l-c$, since they both are strictly decreasing in $c$, they will increase following an adverse shock to aggregate demand.

Next, we consider an adverse shock to labor supply (or equivalently, productive capacity), which is parameterized by a decrease in $l$. On impact, the right hand side of Equation (D.2) increases. Similar to the above reasoning, price $p$ will increase. As $p$ increases, by the second property in Proposition 1 and Proposition 3, product market tightness $\theta$ will increase while consumption (or equivalently, output) $c$ will fall. Again, since both $p$ and $\theta$ increase, according to Equation (10), import price $r$ will rise. As for the matching cost and spare capacity (or equivalently, unemployment), they can be alternatively expressed as:

$$matching\ cost = \frac{\big(1-G(\tau)\big)\big(1-f(\theta)\big)}{1-\big(1-f(\theta)\big)G(\tau)}G(\tau)l,$$

$$spare\ capacity = \frac{1-G(\tau)}{1-G(\tau)+f(\theta)G(\tau)}l,$$

respectively. With $\theta$ increasing and $l$ decreasing following an adverse production shock, it is easy to verify that both the matching cost and spare capacity will decrease.

Lastly, we consider an adverse shock to supply chain, which is represented by an increase in $\gamma$, i.e., the scale parameter of the log-normal distribution of transportation costs $G(.)$. We first look at the effect on price. Using the re-arranged equilibrium condition (D.2), we define

a function $\mathbb{T}:[p^{min},+\infty)\times\mathbb{R}\to\mathbb{R}$:

$$\begin{aligned}\mathbb{T}(p,\gamma)&=\frac{\chi^{\epsilon}}{1+\chi^{\epsilon}}\frac{\mu}{G(\tau)l}-\frac{f(\theta)p}{1-G(\tau)+f(\theta)G(\tau)}\\&=\frac{\chi^{\epsilon}}{1+\chi^{\epsilon}}\frac{\mu}{\Phi(\frac{\log\tau-\gamma}{\sigma})l}-\frac{\big\{1+\big[\frac{1-\eta}{\eta\rho}\big(p-\tau+\beta\int_0^{\tau}\Phi(\frac{\log z'-\gamma}{\sigma})dz'\big)\big]^{-\xi}\big\}^{-\frac{1}{\xi}}p}{1-\Phi(\frac{\log\tau-\gamma}{\sigma})+\big\{1+\big[\frac{1-\eta}{\eta\rho}\big(p-\tau+\beta\int_0^{\tau}\Phi(\frac{\log z'-\gamma}{\sigma})dz'\big)\big]^{-\xi}\big\}^{-\frac{1}{\xi}}\Phi(\frac{\log\tau-\gamma}{\sigma})},\end{aligned}$$

where $\Phi(.)$ is the standard normal cumulative density function. Assuming the existence of a tuple $(p_0,\gamma_0)\in[p^{min},+\infty)\times\mathbb{R}$ such that $\mathbb{T}(p_0,\gamma_0)=0$ and $\partial\mathbb{T}(p,\gamma)/\partial p|_{p=p_0,\gamma=\gamma_0}\neq 0$, by the Implicit Function Theorem, there is a neighborhood of $(p_0,\gamma_0)$ such that whenever $\gamma$ is sufficiently close to $\gamma_0$, there is a unique $p$ so that $\mathbb{T}(p,\gamma)=0$. This assignment makes $p$ a continuous function of $\gamma$. Applying implicit differentiation to $\mathbb{T}(p,\gamma)$ around $(p_0,\gamma_0)$ yields:

$$\frac{dp(\gamma)}{d\gamma}=-\frac{\partial\mathbb{T}(p,\gamma)/\partial\gamma}{\partial\mathbb{T}(p,\gamma)/\partial p}.$$

In terms of $\partial\mathbb{T}(p,\gamma)/\partial\gamma$, we derive that:

$$\begin{aligned}\frac{\partial\mathbb{T}(p,\gamma)}{\partial\gamma}=&\frac{\chi^{\epsilon}}{1+\chi^{\epsilon}}\frac{\mu}{l}\frac{\frac{1}{\sigma}g(\tau)}{G(\tau)^2}+\frac{\big(1-G(\tau)\big)\frac{(1-\eta)\beta}{\eta\rho}\big[\int_0^{\tau}\frac{1}{\sigma}g(z')dz'\big]q(\theta)^{1+\xi}p}{\big(1-G(\tau)+f(\theta)G(\tau)\big)^2}\\&+\frac{\big(1-f(\theta)\big)f(\theta)p\frac{1}{\sigma}g(\tau)}{\big(1-G(\tau)+f(\theta)G(\tau)\big)^2}>0,\end{aligned}$$

where $g(\tau)\equiv\phi[(\log\tau-\gamma)/\sigma]$, $g(z')\equiv\phi[(\log z'-\gamma)/\sigma]$, while $\phi(.)$ is the standard normal probability density function. In terms of $\partial\mathbb{T}(p,\gamma)/\partial p$, it can be written as:

$$\frac{\partial\mathbb{T}(p,\gamma)}{\partial p}=-\frac{\big(1-G(\tau)\big)\frac{1-\eta}{\eta\rho}q(\theta)^{1+\xi}p+f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)}{\big(1-G(\tau)+f(\theta)G(\tau)\big)^2}<0.$$

By combining $\partial\mathbb{T}(p,\gamma)/\partial\gamma$ with $\partial\mathbb{T}(p,\gamma)/\partial p$ and collecting terms, we have:

$$\begin{aligned}\frac{dp(\gamma)}{d\gamma}=&\big[\big(1-G(\tau)\big)\frac{1-\eta}{\eta\rho}q(\theta)^{1+\xi}p+f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)\big]^{-1}\\&\cdot\big\{\big(1-G(\tau)+f(\theta)G(\tau)\big)f(\theta)\frac{1}{\sigma}g(\tau)\frac{p}{G(\tau)}\\&+\big(1-G(\tau)\big)\frac{(1-\eta)\beta}{\eta\rho}\big[\int_0^{\tau}\frac{1}{\sigma}g(z')dz'\big]q(\theta)^{1+\xi}p\\&+\big(1-f(\theta)\big)f(\theta)p\frac{1}{\sigma}g(\tau)\big\}>0.\end{aligned}\tag{D.3}$$

Hence, price $p$ will increase on impact of an adverse shock to supply chain. In terms of

consumption (or equivalently, output), it is written as:

$$c(\gamma) = \frac{\chi^{\epsilon}}{1+\chi^{\epsilon}} \frac{\mu}{p(\gamma)},$$

where $p$ is an implicit function of $\gamma$. Therefore, the derivative of $c$ with respect to $\gamma$ is:

$$\begin{aligned}
\frac{dc(\gamma)}{d\gamma} = &- \frac{\chi^{\epsilon}}{1+\chi^{\epsilon}} \frac{\mu}{p} \big[ \big(1-G(\tau)\big) \frac{1-\eta}{\eta\rho} q(\theta)^{1+\xi} p + f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big) \big]^{-1} \\
&\cdot \Big\{ \big(1-G(\tau)+f(\theta)G(\tau)\big) f(\theta) \frac{1}{\sigma} g(\tau) \frac{1}{G(\tau)} \\
&+ \big(1-G(\tau)\big) \frac{(1-\eta)\beta}{\eta\rho} \big[ \int_0^{\tau} \frac{1}{\sigma} g(z')dz' \big] q(\theta)^{1+\xi} \\
&+ \big(1-f(\theta)\big) f(\theta) \frac{1}{\sigma} g(\tau) \Big\} < 0.
\end{aligned}$$

Hence, consumption (or equivalently, output) $c$ will fall. Next, in terms of product market tightness, it is given by:

$$\theta(\gamma) = \frac{1-\eta}{\eta\rho} \big( p(\gamma) - \tau + \beta \int_0^{\tau} \Phi(\frac{\log z' - \gamma}{\sigma}) dz' \big). \tag{D.4}$$

Accordingly, the derivative of $\theta$ with respect to $\gamma$ is:

$$\begin{aligned}
\frac{d\theta(\gamma)}{d\gamma} = &\frac{1-\eta}{\eta\rho} \big[ \big(1-G(\tau)\big) \frac{1-\eta}{\eta\rho} q(\theta)^{1+\xi} p + f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big) \big]^{-1} \\
&\cdot \Big\{ \big(1-G(\tau)+f(\theta)G(\tau)\big) f(\theta) \frac{1}{\sigma} g(\tau) \frac{p}{G(\tau)} + \big(1-f(\theta)\big) f(\theta) p \frac{1}{\sigma} g(\tau) \\
&- \big(1-G(\tau)+f(\theta)G(\tau)\big) f(\theta) \beta \big[ \int_0^{\tau} \frac{1}{\sigma} g(z')dz' \big] \Big\},
\end{aligned} \tag{D.5}$$

whose value depends on the values of $\theta$ and $p$; as we will discuss later in Appendix D.5, this dependence is crucial for the state-dependence result of a contractionary monetary policy shock. Similarly, by substituting Equation (D.4) into Equation (10), the import price can be expressed as:

$$r(\gamma) = p(\gamma) + (1-\eta)\beta \int_0^{\tau} \Phi(\frac{\log z' - \gamma}{\sigma}) dz' + (1-\eta)(z-\tau).$$

Differentiating $r(\gamma)$ with respect to $\gamma$ yields:

$$\begin{aligned}\frac{dr(\gamma)}{d\gamma} =&\big[\big(1-G(\tau)\big)\frac{1-\eta}{\eta\rho}q(\theta)^{1+\xi}p + f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)\big]^{-1}\\ &\cdot\Big\{\big(1-G(\tau)+f(\theta)G(\tau)\big)f(\theta)\frac{1}{\sigma}g(\tau)\frac{p}{G(\tau)}\\ &+\big(1-G(\tau)\big)\frac{(1-\eta)\beta}{\rho}\big[\int_0^\tau \frac{1}{\sigma}g(z')dz'\big]q(\theta)^{1+\xi}p\\ &+\big(1-f(\theta)\big)f(\theta)p\frac{1}{\sigma}g(\tau)\\ &-\big(1-G(\tau)+f(\theta)G(\tau)\big)f(\theta)(1-\eta)\beta\big[\int_0^\tau \frac{1}{\sigma}g(z')dz'\big]\Big\},\end{aligned}$$

whose value is also dependent on the values of $\theta$ and $p$. As for the matching cost, given that it is measured by the difference between $G(\tau)l$ and $c$, its derivative with respect to $\gamma$ can be written as:

$$\begin{aligned}\frac{d}{d\gamma}\big[\textit{matching cost}(\gamma)\big] =&\big[\big(1-G(\tau)\big)\frac{1-\eta}{\eta\rho}q(\theta)^{1+\xi}p + f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)\big]^{-1}\\ &\cdot\Big(\frac{\chi^\epsilon}{1+\chi^\epsilon}\frac{\mu}{p}\Big\{\big(1-G(\tau)+f(\theta)G(\tau)\big)f(\theta)\frac{1}{\sigma}g(\tau)\frac{1}{G(\tau)}\\ &+\big(1-G(\tau)\big)\frac{(1-\eta)\beta}{\eta\rho}\big[\int_0^\tau \frac{1}{\sigma}g(z')dz'\big]q(\theta)^{1+\xi}\\ &+\big(1-f(\theta)\big)f(\theta)\frac{1}{\sigma}g(\tau)\Big\}\\ &-\big(1-G(\tau)\big)\frac{1-\eta}{\eta\rho}q(\theta)^{1+\xi}p\frac{1}{\sigma}g(\tau)l\\ &-f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)\frac{1}{\sigma}g(\tau)l\Big),\end{aligned}$$

whose value is again dependent on the values of $\theta$ and $p$. On the contrary, since the spare capacity (or equivalently, unemployment) is measured by the difference between $l$ and $c$, its derivative with respect to $\gamma$ is positive, i.e.,

$$\begin{aligned}\frac{d}{d\gamma}\big[\textit{spare capacity}(\gamma)\big] =&\frac{\chi^\epsilon}{1+\chi^\epsilon}\frac{\mu}{p}\big[\big(1-G(\tau)\big)\frac{1-\eta}{\eta\rho}q(\theta)^{1+\xi}p + f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)\big]^{-1}\\ &\cdot\Big\{\big(1-G(\tau)+f(\theta)G(\tau)\big)f(\theta)\frac{1}{\sigma}g(\tau)\frac{1}{G(\tau)}\\ &+\big(1-G(\tau)\big)\frac{(1-\eta)\beta}{\eta\rho}\big[\int_0^\tau \frac{1}{\sigma}g(z')dz'\big]q(\theta)^{1+\xi}\\ &+\big(1-f(\theta)\big)f(\theta)\frac{1}{\sigma}g(\tau)\Big\} > 0.\end{aligned}$$

## D.5. Proof of Proposition 6

We start the proof by re-visiting the function $\mathbb{T} : [p^{min}, +\infty) \times \mathbb{R}^+ \times \mathbb{R} \to \mathbb{R}$:

$$\mathbb{T}(p,\mu,\gamma) = \frac{\chi^\epsilon}{1+\chi^\epsilon}\frac{\mu}{G(\tau)l} - \frac{f(\theta)p}{1-G(\tau)+f(\theta)G(\tau)}$$
$$= \frac{\chi^\epsilon}{1+\chi^\epsilon}\frac{\mu}{\Phi(\frac{\log\tau-\gamma}{\sigma})l} - \frac{\left\{1+\left[\frac{1-\eta}{\eta\rho}\left(p-\tau+\beta\int_0^\tau\Phi(\frac{\log z'-\gamma}{\sigma})dz'\right)\right]^{-\xi}\right\}^{-\frac{1}{\xi}}p}{1-\Phi(\frac{\log\tau-\gamma}{\sigma})+\left\{1+\left[\frac{1-\eta}{\eta\rho}\left(p-\tau+\beta\int_0^\tau\Phi(\frac{\log z'-\gamma}{\sigma})dz'\right)\right]^{-\xi}\right\}^{-\frac{1}{\xi}}\Phi(\frac{\log\tau-\gamma}{\sigma})},$$

where $\Phi(.)$ is the standard normal cumulative density function. Subsequently, assuming the existence of a tuple $(p_0,\mu_0,\gamma_0) \in [p^{min},+\infty)\times\mathbb{R}^+\times\mathbb{R}$ such that $\mathbb{T}(p_0,\mu_0,\gamma_0)=0$ and $\partial\mathbb{T}(p,\mu,\gamma)/\partial p|_{p=p_0,\mu=\mu_0,\gamma=\gamma_0} \neq 0$, by the Implicit Function Theorem, there is a neighborhood of $(p_0,\mu_0,\gamma_0)$ such that whenever $(\mu,\gamma)$ is sufficiently close to $(\mu_0,\gamma_0)$, there is a unique $p$ so that $\mathbb{T}(p,\mu,\gamma)=0$. This assignment makes $p$ a continuous function of $\mu$ and $\gamma$. Applying implicit differentiation to $\mathbb{T}(p,\mu,\gamma)$ around $(p_0,\mu_0,\gamma_0)$ yields:

$$\frac{\partial p(\mu,\gamma)}{\partial\mu} = -\frac{\partial\mathbb{T}(p,\mu,\gamma)/\partial\mu}{\partial\mathbb{T}(p,\mu,\gamma)/\partial p}.$$

The numerator can be written as:

$$\frac{\partial\mathbb{T}(p,\mu,\gamma)}{\partial\mu} = \frac{\chi^\epsilon}{1+\chi^\epsilon}\frac{1}{G(\tau)l} > 0,$$

whereas the denominator is given by:

$$\frac{\partial\mathbb{T}(p,\mu,\gamma)}{\partial p} = -\frac{\big(1-G(\tau)\big)\frac{1-\eta}{\eta\rho}q(\theta)^{1+\xi}p + f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)}{\big(1-G(\tau)+f(\theta)G(\tau)\big)^2} < 0.$$

By combining $\partial\mathbb{T}(p,\mu,\gamma)/\partial\mu$ with $\partial\mathbb{T}(p,\mu,\gamma)/\partial p$, we derive that:

$$\frac{\partial p(\mu,\gamma)}{\partial\mu} = \frac{\chi^\epsilon}{1+\chi^\epsilon}\frac{1}{G(\tau)l}\frac{\big(1-G(\tau)+f(\theta)G(\tau)\big)^2}{\big(1-G(\tau)\big)\frac{1-\eta}{\eta\rho}q(\theta)^{1+\xi}p + f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)}$$
$$= \frac{1}{\mu}\left[\frac{\big(1-G(\tau)\big)\frac{1-\eta}{\eta\rho}q(\theta)^{1+\xi}}{f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)} + \frac{1}{p}\right]^{-1} > 0.$$

In terms of the partial derivative $\partial c(\mu,\gamma)/\partial\mu$, using the expression of the aggregate demand in Equation (20), we can derive that:

$$\begin{aligned}\frac{\partial c(\mu,\gamma)}{\partial\mu} &= \frac{\chi^{\epsilon}}{1+\chi^{\epsilon}}\frac{\big(1-G(\tau)\big)^{\frac{1-\eta}{\eta\rho}}q(\theta)^{1+\xi}}{\big(1-G(\tau)\big)^{\frac{1-\eta}{\eta\rho}}q(\theta)^{1+\xi}p+f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)}\\ &= \frac{\chi^{\epsilon}}{1+\chi^{\epsilon}}\Big[p+\frac{f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)}{\big(1-G(\tau)\big)^{\frac{1-\eta}{\eta\rho}}q(\theta)^{1+\xi}}\Big]^{-1}.\end{aligned}$$

Hence, both $\partial p(\mu,\gamma)/\partial\mu$ and $\partial c(\mu,\gamma)/\partial\mu$ depend on the fraction:

$$\frac{\big(1-G(\tau)\big)^{\frac{1-\eta}{\eta\rho}}q(\theta)^{1+\xi}}{f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)}. \tag{D.6}$$

Next, we study the dependence of the fraction (D.6) on $\gamma$, as it directly determines the signs of $\partial^2 p(\mu,\gamma)/\partial\mu\partial\gamma$ and $\partial^2 c(\mu,\gamma)/\partial\mu\partial\gamma$. It is given by:

$$\begin{aligned}&\frac{\partial}{\partial\gamma}\Big[\frac{\big(1-G(\tau)\big)^{\frac{1-\eta}{\eta\rho}}q(\theta)^{1+\xi}}{f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)}\Big] = \frac{f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)\big[\frac{1}{\sigma}g(\tau)^{\frac{1-\eta}{\eta\rho}}q(\theta)^{1+\xi}\big]}{\big[f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)\big]^2}\\ &-\frac{f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)\big[\big(1-G(\tau)\big)^{\frac{1-\eta}{\eta\rho}}\frac{\partial\theta(\mu,\gamma)}{\partial\gamma}(1+\xi)\theta^{\xi-1}(1+\theta^{\xi})^{-\frac{1+\xi}{\xi}-1}\big]}{\big[f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)\big]^2}\\ &-\frac{\big(1-G(\tau)\big)^{\frac{1-\eta}{\eta\rho}}q(\theta)^{1+\xi}\big[\frac{\partial\theta(\mu,\gamma)}{\partial\gamma}q(\theta)^{1+\xi}\big(1-G(\tau)+f(\theta)G(\tau)\big)\big]}{\big[f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)\big]^2}\\ &-\frac{\big(1-G(\tau)\big)^{\frac{1-\eta}{\eta\rho}}q(\theta)^{1+\xi}\big[f(\theta)\big(\frac{1}{\sigma}g(\tau)+\frac{\partial\theta(\mu,\gamma)}{\partial\gamma}q(\theta)^{1+\xi}G(\tau)-f(\theta)\frac{1}{\sigma}g(\tau)\big)\big]}{\big[f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)\big]^2},\end{aligned}$$

and is proportional to:

$$\begin{aligned}&\frac{\partial}{\partial\gamma}\Big[\frac{\big(1-G(\tau)\big)^{\frac{1-\eta}{\eta\rho}}q(\theta)^{1+\xi}}{f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)}\Big] \propto f(\theta)^2\frac{1}{\sigma}g(\tau)\\ &-f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)\big(1-G(\tau)\big)\frac{\partial\theta(\mu,\gamma)}{\partial\gamma}(1+\xi)\frac{\theta^{\xi-1}}{1+\theta^{\xi}}\\ &-\big(1-G(\tau)\big)\frac{\partial\theta(\mu,\gamma)}{\partial\gamma}q(\theta)^{1+\xi}\big(1-G(\tau)+f(\theta)G(\tau)\big)\\ &-\big(1-G(\tau)\big)f(\theta)\frac{\partial\theta(\mu,\gamma)}{\partial\gamma}q(\theta)^{1+\xi}G(\tau),\end{aligned}$$

where $g(\tau)\equiv\phi[(\log\tau-\gamma)/\sigma]$ and $\phi(.)$ is the standard normal probability density function.

When the partial derivative of $\theta$ with respect to $\gamma$ satisfies:

$$\frac{\partial\theta(\mu,\gamma)}{\partial\gamma} > \frac{f(\theta)^2\frac{1}{\sigma}g(\tau)}{\big(1-G(\tau)\big)f(\theta)q(\theta)^{1+\xi}G(\tau)} = \frac{\theta(1+\theta^{\xi})\frac{1}{\sigma}g(\tau)}{\big(1-G(\tau)\big)G(\tau)} > 0,$$

it is easy to verify that:

$$\frac{\partial}{\partial\gamma}\Big[\frac{\big(1-G(\tau)\big)\frac{1-\eta}{\eta\rho}q(\theta)^{1+\xi}}{f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)}\Big] < 0,$$

and the values of the cross derivatives can thus be determined:

$$\begin{aligned}\frac{\partial^2 p(\mu,\gamma)}{\partial\mu\partial\gamma} = &-\Big\{\frac{\partial}{\partial\gamma}\Big[\frac{\big(1-G(\tau)\big)\frac{1-\eta}{\eta\rho}q(\theta)^{1+\xi}}{f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)}\Big] - \frac{\partial p(\mu,\gamma)}{\partial\gamma}\frac{1}{p^2}\Big\}\\ &\cdot\Big[\frac{\big(1-G(\tau)\big)\frac{1-\eta}{\eta\rho}q(\theta)^{1+\xi}}{f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)}+\frac{1}{p}\Big]^{-2}\frac{1}{\mu} > 0,\end{aligned}$$

$$\begin{aligned}\frac{\partial^2 c(\mu,\gamma)}{\partial\mu\partial\gamma} = &-\Big\{\frac{\partial p(\mu,\gamma)}{\partial\gamma} - \frac{\partial}{\partial\gamma}\Big[\frac{\big(1-G(\tau)\big)\frac{1-\eta}{\eta\rho}q(\theta)^{1+\xi}}{f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)}\Big]\Big[\frac{\big(1-G(\tau)\big)\frac{1-\eta}{\eta\rho}q(\theta)^{1+\xi}}{f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)}\Big]^{-2}\Big\}\\ &\cdot\Big[p+\frac{f(\theta)\big(1-G(\tau)+f(\theta)G(\tau)\big)}{\big(1-G(\tau)\big)\frac{1-\eta}{\eta\rho}q(\theta)^{1+\xi}}\Big]^{-2}\frac{\chi^{\epsilon}}{1+\chi^{\epsilon}} < 0,\end{aligned}$$

where $\partial p(\mu,\gamma)/\partial\gamma > 0$ according to Equation (D.3). With them, it is straightforward to derive the rest of the cross derivatives: specifically, for the product market tightness,

$$\frac{\partial\theta(\mu,\gamma)}{\partial\mu} = \frac{1-\eta}{\eta\rho}\frac{\partial p(\mu,\gamma)}{\partial\mu} > 0,\ \ \frac{\partial^2\theta(\mu,\gamma)}{\partial\mu\partial\gamma} = \frac{1-\eta}{\eta\rho}\frac{\partial^2 p(\mu,\gamma)}{\partial\mu\partial\gamma} > 0;$$

for the import price,

$$\frac{\partial r(\mu,\gamma)}{\partial\mu} = \frac{\partial p(\mu,\gamma)}{\partial\mu} > 0,\ \ \frac{\partial^2 r(\mu,\gamma)}{\partial\mu\partial\gamma} = \frac{\partial^2 p(\mu,\gamma)}{\partial\mu\partial\gamma} > 0;$$

for the matching cost,

$$\frac{\partial}{\partial\mu}\big[\textit{matching cost}(\mu,\gamma)\big] = -\frac{\partial c(\mu,\gamma)}{\partial\mu} < 0,\ \ \frac{\partial^2}{\partial\mu\partial\gamma}\big[\textit{matching cost}(\mu,\gamma)\big] = -\frac{\partial^2 c(\mu,\gamma)}{\partial\mu\partial\gamma} > 0;$$

and lastly, for the spare capacity (or equivalently, unemployment),

$$\frac{\partial}{\partial\mu}\big[\textit{spare capacity}(\mu,\gamma)\big] = -\frac{\partial c(\mu,\gamma)}{\partial\mu} < 0,\ \ \frac{\partial^2}{\partial\mu\partial\gamma}\big[\textit{spare capacity}(\mu,\gamma)\big] = -\frac{\partial^2 c(\mu,\gamma)}{\partial\mu\partial\gamma} > 0.$$

# E. Fixed-Price Aggregate Supply

In contrast to the flexible-price aggregate supply as discussed in the main text, we consider here the alternative pricing mechanism in which the price of goods is fixed while the reservation transportation cost can vary. A careful exposition of such a fixed-price mechanism is essential to understand how the matching frictions and endogenous separation mechanism could affect aggregate supply differently. The fixed-price aggregate supply is defined below, and its key analytical properties are summarized in Proposition 2′.

**Definition 2″.** *For an arbitrary price $\kappa \in (0, +\infty)$, the fixed-price aggregate supply $c_s^{fix}$ is the function of reservation transportation cost $\bar{z}$ defined by:*

$$c_s^{fix}(\bar{z}) = \frac{\left\{1 + \left[\frac{1-\eta}{\eta\rho}\left(\kappa - \bar{z} + \beta \int_0^{\bar{z}} G(z')dz'\right)\right]^{-\xi}\right\}^{-\frac{1}{\xi}} G(\bar{z})l}{1 - G(\bar{z}) + \left\{1 + \left[\frac{1-\eta}{\eta\rho}\left(\kappa - \bar{z} + \beta \int_0^{\bar{z}} G(z')dz'\right)\right]^{-\xi}\right\}^{-\frac{1}{\xi}} G(\bar{z})}, \tag{E.1}$$

*for all $\bar{z} \in (0, \bar{z}^{max}]$, where $\bar{z}^{max}$ satisfies:*

$$\kappa - \bar{z}^{max} + \beta \int_0^{\bar{z}^{max}} G(z')dz' = 0. \tag{E.2}$$

**Proposition 2′.** *The fixed-price aggregate supply $c_s^{fix}$ has the following properties:*

1. $\lim_{\bar{z}\to 0^+} c_s^{fix}(\bar{z}) = 0$;
2. $c_s^{fix}(\bar{z}^{max}) = 0$; *and*
3. *There exists at least one $\bar{z}^* \in (0, \bar{z}^{max}]$ such that $dc_s^{fix}(\bar{z})/d\bar{z}|_{\bar{z}=\bar{z}^*} = 0$.*

*Proof.* It is straightforward to prove the first property. When $\bar{z} \to 0^+$, $\lim_{\bar{z}\to 0^+} \theta(\bar{z}) = (1-\eta)\kappa/(\eta\rho)$, $\lim_{\bar{z}\to 0^+} f\big(\theta(\bar{z})\big) = \{1 + [(1-\eta)\kappa/(\eta\rho)]^{-\xi}\}^{-1/\xi} > 0$. At the same time, when $\bar{z} \to 0^+$, $\lim_{\bar{z}\to 0^+} G(\bar{z}) = 0$. Therefore, $\lim_{\bar{z}\to 0^+} c_s^{fix}(\bar{z}) = 0$. In terms of the second property, it is obvious from the definition of $\bar{z}^{max}$, together with that $f(0) = 0$. Regarding the last

property, the derivative of $c_s^{fix}$ with respect to $\bar{z}$ can be written as:

$$\frac{dc_s^{fix}(\bar{z})}{d\bar{z}} = \big(1 - G(\bar{z}) + f(\theta)G(\bar{z})\big)^{-2} \cdot \Big[ \underbrace{\big(1 - G(\bar{z})\big)\frac{1-\eta}{\eta\rho}\big(-1 + \beta G(\bar{z})\big)\theta^{-\xi-1}f(\theta)^{1+\xi}G(\bar{z})l}_{\substack{\text{Product Market Tightness} \\ \text{Channel} < 0}} + \underbrace{f(\theta)\frac{1}{\bar{z}\sigma}g(\bar{z})l}_{\substack{\text{Separation Margin} \\ \text{Channel} > 0}} \Big],$$

where $G(\bar{z}) \equiv \Phi[(\log \bar{z} - \gamma)/\sigma]$, $g(\bar{z}) \equiv \phi[(\log \bar{z} - \gamma)/\sigma]$, while $\Phi(.)$ and $\phi(.)$ are the standard normal cumulative density function and probability density function respectively. The product market tightness channel is negative, because a higher reservation transportation cost would reduce the total surplus to be shared between exporters and importers at the margin, hence dampening the incentives for importers to visit exporters, leading to a slack product market as well as a lower aggregate supply. The separation margin channel is positive, because a larger proportion of matches that would otherwise have been dismissed could now continue, hence contributing to a higher aggregate supply. These two channels jointly determine the fixed-price aggregate supply, and the extent to which one channel dominates the other depends on both the parameter values and reservation transportation cost itself.

When $\bar{z} \to 0^+$, it can be shown that:

$$\lim_{\bar{z}\to 0^+} \frac{dc_s^{fix}(\bar{z})}{d\bar{z}} = \Big\{1 + \Big[\frac{(1-\eta)\kappa}{\eta\rho}\Big]^{-\xi}\Big\}^{-\frac{1}{\xi}} \lim_{\bar{z}\to 0^+} \frac{1}{\bar{z}\sigma} g(\bar{z})l > 0,$$

since the probability density function of a log-normal distribution is always positive. When $\bar{z} \to \bar{z}^{max}$, it can be derived that:

$$\lim_{\bar{z}\to \bar{z}^{max}} \frac{dc_s^{fix}(\bar{z})}{d\bar{z}} = \frac{1}{1 - G(\bar{z}^{max})} \frac{1-\eta}{\eta\rho}\big(-1 + \beta G(\bar{z}^{max})\big)G(\bar{z}^{max})l < 0.$$

Consider an infinitesimal number $\epsilon > 0$ such that $dc_s^{fix}(\bar{z})/d\bar{z}|_{\bar{z}=\epsilon}$ and $\lim_{\bar{z}\to 0^+} dc_s^{fix}(\bar{z})/d\bar{z}$ have the same sign. By the Intermediate Value Theorem, since $dc_s^{fix}(\bar{z})/d\bar{z}$ is continuous on $[\epsilon, \bar{z}^{max}]$, there must exist at least one $\bar{z}^* \in [\epsilon, \bar{z}^{max}]$ such that $dc_s^{fix}(\bar{z})/d\bar{z}|_{\bar{z}=\bar{z}^*} = 0$. Since $[\epsilon, \bar{z}^{max}]$ is a sub-interval of $(0, \bar{z}^{max}]$, the last property thus holds. ■

To plot the fixed-price aggregate supply, we also need to pin down its curvature. Since the value of the second derivative of $c_s^{fix}$ cannot be determined analytically, we resort to

numerical methods for an approximation.[8] Figure E.1 plots the fixed-price aggregate supply, its theoretical upper bound if the matching frictions were absent, and the productive capacity. As seen, the non-monotonic behavior of the fixed-price aggregate supply clearly illustrates the two aforementioned, counteracting channels at play; specifically, when the reservation transportation cost is relatively low, the separation margin channel dominates the product market tightness channel, and vice versa. Therefore, there exists a level of reservation transportation cost such that the aggregate supply is maximized. Such a behavior is similar to the one considered in Michaillat and Saez (2015), where both the matching frictions on the product market and matching cost per visit give rise to the non-standard behavior of the aggregate supply curve.[9]

In terms of the other variables of interest, as the reservation transportation cost increases, the matching cost, i.e., $G(\bar{z})l-c$, increases, the transportation cost, i.e., $(1-G(\bar{z}))l$, decreases, while the spare capacity (or equivalently, unemployment), i.e., $l-c$, first decreases then increases.

8. Nevertheless, the second derivative of $c_s^{fix}$ with respect to $\bar{z}$ is given by:

$$\frac{d^2c_s^{fix}(\bar{z})}{d\bar{z}^2} = \big(1-G(\bar{z})+f(\theta)G(\bar{z})\big)^2\cdot\Big(\frac{(1-\eta)l}{\eta\rho}\frac{1}{\bar{z}\sigma}g(\bar{z})\big(-1+2\beta G(\bar{z})+2G(\bar{z})-3\beta G(\bar{z})^2\big)q(\theta)^{1+\xi}$$
$$-\frac{(1-\eta)l}{\eta\rho}\big(1-G(\bar{z})\big)G(\bar{z})\big(-1+\beta G(\bar{z})\big)^2\frac{1-\eta}{\eta\rho}\theta^{\xi-1}(1+\xi)\big(1+\theta^{\xi}\big)^{-\frac{1+\xi}{\xi}-1}$$
$$+\frac{1-\eta}{\eta\rho}\big(-1+\beta G(\bar{z})\big)\theta^{-\xi-1}\big(1+\theta^{-\xi}\big)^{-\frac{1}{\xi}-1}\frac{1}{\bar{z}\sigma}g(\bar{z})l-f(\theta)l\Big\{\frac{1}{\bar{z}^2\sigma}g(\bar{z})+\frac{\log\bar{z}-\gamma}{\bar{z}^2\sigma^3\sqrt{2\pi}}\exp\Big[-\frac{(\log\bar{z}-\gamma)^2}{2\sigma^2}\Big]\Big\}\Big)$$
$$-\Big[\frac{(1-\eta)l}{\eta\rho}\big(1-G(\bar{z})\big)G(\bar{z})\big(-1+\beta G(\bar{z})\big)q(\theta)^{1+\xi}+f(\theta)\frac{1}{\bar{z}\sigma}g(\bar{z})l\Big]$$
$$\cdot\Big[\frac{1-\eta}{\eta\rho}\big(-1+\beta G(\bar{z})\big)\theta^{-\xi-1}\big(1+\theta^{-\xi}\big)^{-\frac{1}{\xi}-1}G(\bar{z})-\big(1-f(\theta)\big)\frac{1}{\bar{z}\sigma}g(\bar{z})\Big]2\big(1-G(\bar{z})+f(\theta)G(\bar{z})\big),$$

9. In contrast to our fixed-price aggregate supply curve which is plotted in the $(c,\bar{z})$ plane, the aggregate supply curve in Michaillat and Saez (2015) is plotted in the $(c,x)$ plane, where $x$ refers to the product market tightness. See Figure I of their paper for details.

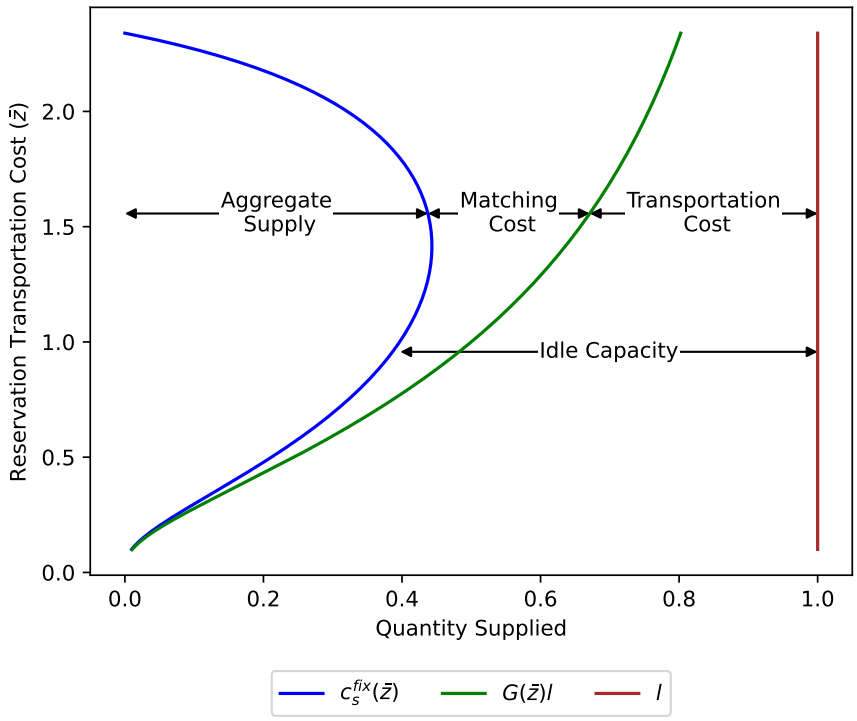



**Figure E.1:** Supply Side of the Economy When the Price of Goods Is Fixed

*Notes.* The figure plots the fixed-price aggregate supply $c_s^{fix}(\bar{z})$, its theoretical upper bound if the matching frictions were absent $G(\bar{z})l$, and the productive capacity $l$ for certain values of reservation transportation cost $\bar{z}$. The gap between $c_s^{fix}(\bar{z})$ and $G(\bar{z})l$ represents the matching cost, the gap between $G(\bar{z})l$ and $l$ represents the transportation cost (measured in units of goods), whereas the gap between $c_s^{fix}(\bar{z})$ and $l$ represents the spare capacity of exporters, or equivalently, the unemployment. In the numerical approximation, parameter values are $\eta = 0.5, \rho = 0.5, \kappa = 1.2, \beta = 0.99, \xi = 2, l = 1, \gamma = 0$, and $\sigma = 1$. $\bar{z}$ takes its values from 1,000 evenly spaced numbers over $[0.1, \bar{z}^{max}]$, where $\bar{z}^{max}$ is solved numerically using its definition in (E.2).

# F. Robustness of SVAR Results

## F.1. Different Lag Structures and Longer Restrictions

In Figures F.1 to F.6, we show that our baseline results are robust to considering different lag structures, i.e., one or three lags. We do not consider four lags or beyond due to parameter uncertainty resulting from our limited sample length. We also extend the horizons at which we impose the sign restrictions – i.e., from $k = 1$ to $k = 1, 2$ – so as to put more disciplines on the behaviors of the IRFs. As shown in Figures F.7 to F.9, our baseline results still hold.

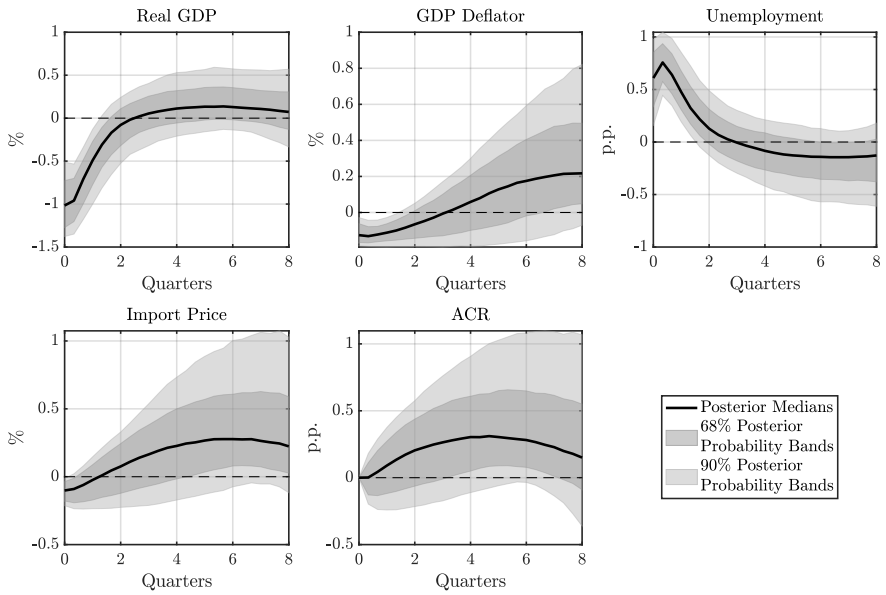



**Figure F.1:** IRFs to an Adverse Shock to Aggregate Demand: $L = 1$

*Notes.* The IRFs to a one standard deviation adverse shock to aggregate demand are identified using an SVAR specification as in Equation (24) with one lag, as well as Restrictions 1, 2, and 3. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. The figure is based on 100,000 independent draws.

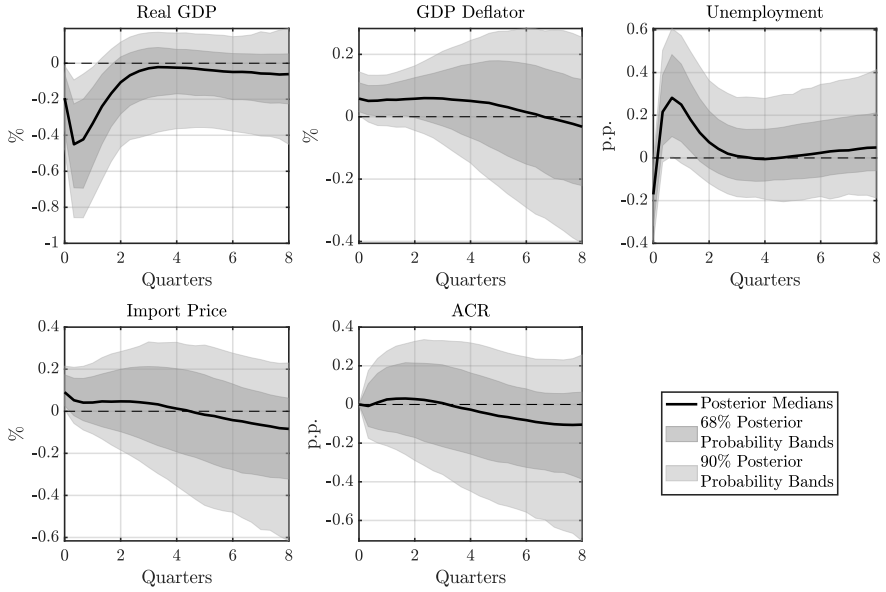



**Figure F.2:** IRFs to an Adverse Shock to Labor Supply: $L = 1$

*Notes.* The IRFs to a one standard deviation adverse shock to labor supply are identified using an SVAR specification as in Equation (24) with one lag, as well as Restrictions 1, 2, and 3. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. The figure is based on 100,000 independent draws.

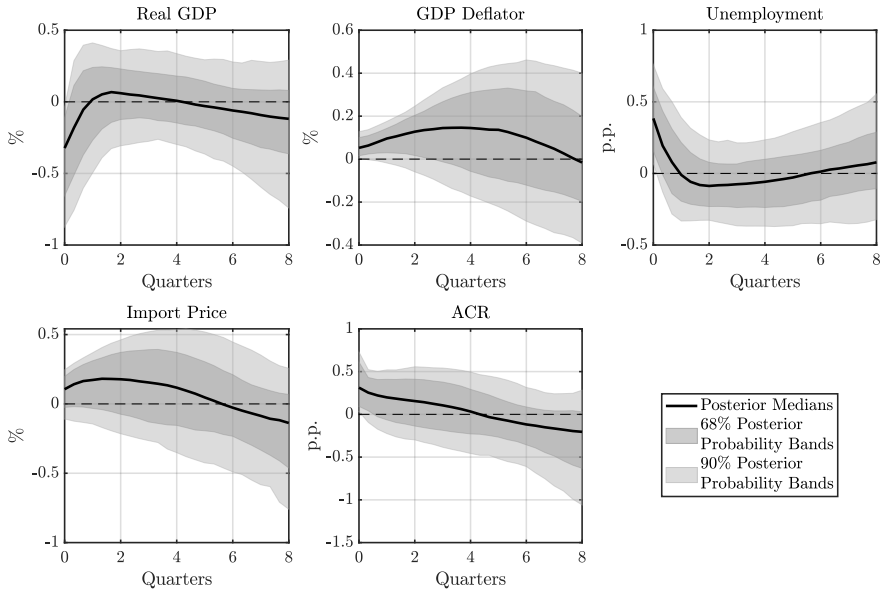



**Figure F.3:** IRFs to an Adverse Shock to Supply Chain: $L = 1$

*Notes.* The IRFs to a one standard deviation adverse shock to supply chain are identified using an SVAR specification as in Equation (24) with one lag, as well as Restrictions 1, 2, and 3. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. The figure is based on 100,000 independent draws.

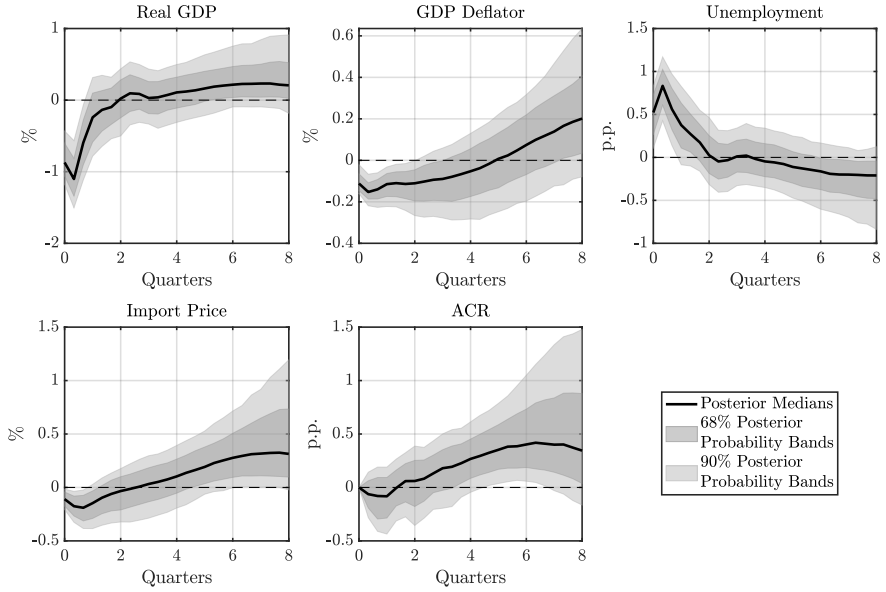



**Figure F.4:** IRFs to an Adverse Shock to Aggregate Demand: $L = 3$

*Notes.* The IRFs to a one standard deviation adverse shock to aggregate demand are identified using an SVAR specification as in Equation (24) with three lags, as well as Restrictions 1, 2, and 3. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. The figure is based on 100,000 independent draws.

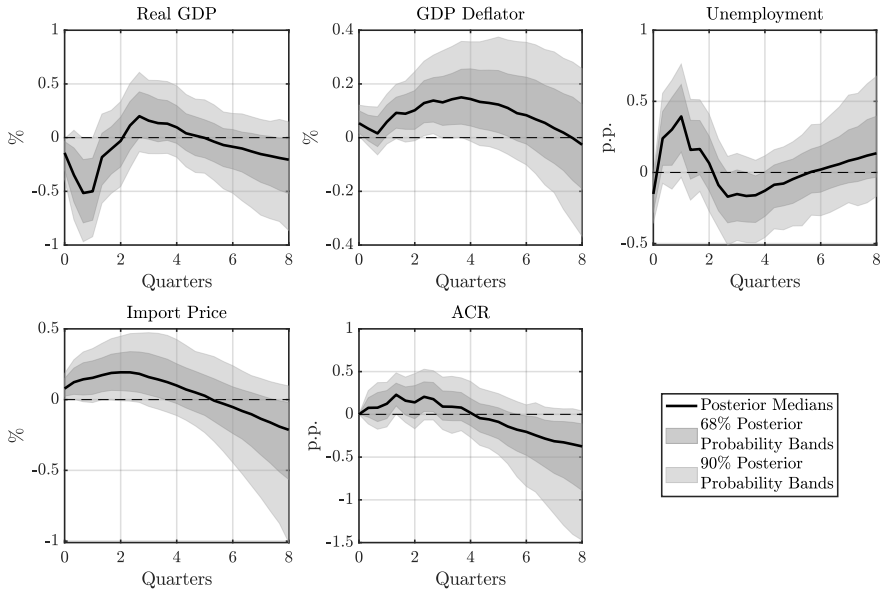



**Figure F.5:** IRFs to an Adverse Shock to Labor Supply: $L = 3$

*Notes.* The IRFs to a one standard deviation adverse shock to labor supply are identified using an SVAR specification as in Equation (24) with three lags, as well as Restrictions 1, 2, and 3. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. The figure is based on 100,000 independent draws.

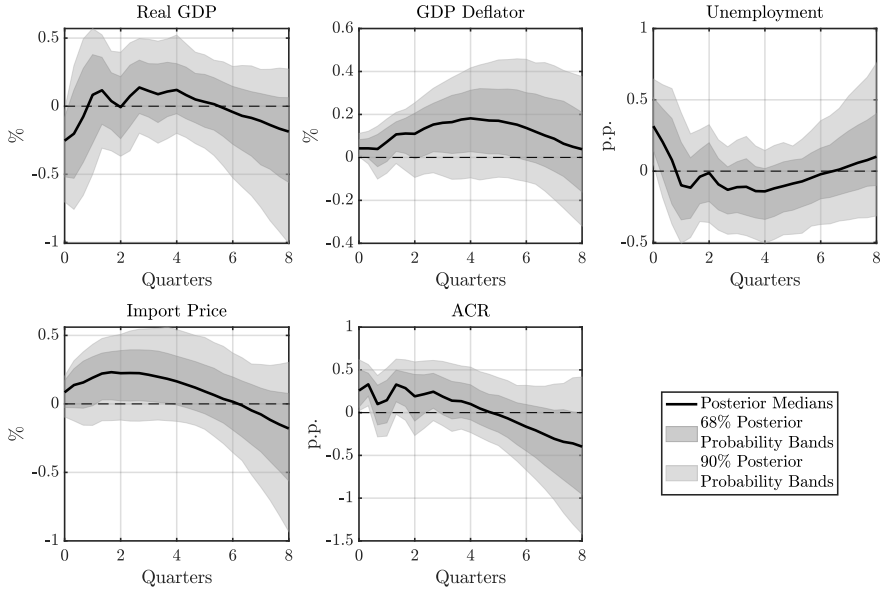



**Figure F.6:** IRFs to an Adverse Shock to Supply Chain: $L = 3$

*Notes.* The IRFs to a one standard deviation adverse shock to supply chain are identified using an SVAR specification as in Equation (24) with three lags, as well as Restrictions 1, 2, and 3. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. The figure is based on 100,000 independent draws.

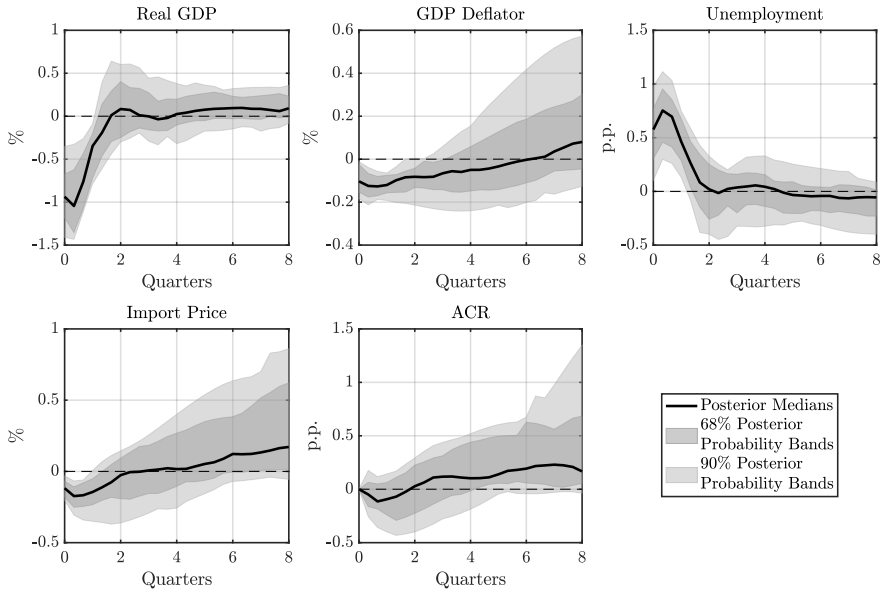



**Figure F.7:** IRFs to an Adverse Shock to Aggregate Demand: $k = 1, 2$

*Notes.* The IRFs to a one standard deviation adverse shock to aggregate demand are identified using a set of restrictions that are the same as Restrictions 1, 2, and 3, except that the sign restrictions on IRFs are imposed for longer horizons, i.e., $k = 1$ to $k = 1, 2$. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. The figure is based on 100,000 independent draws.

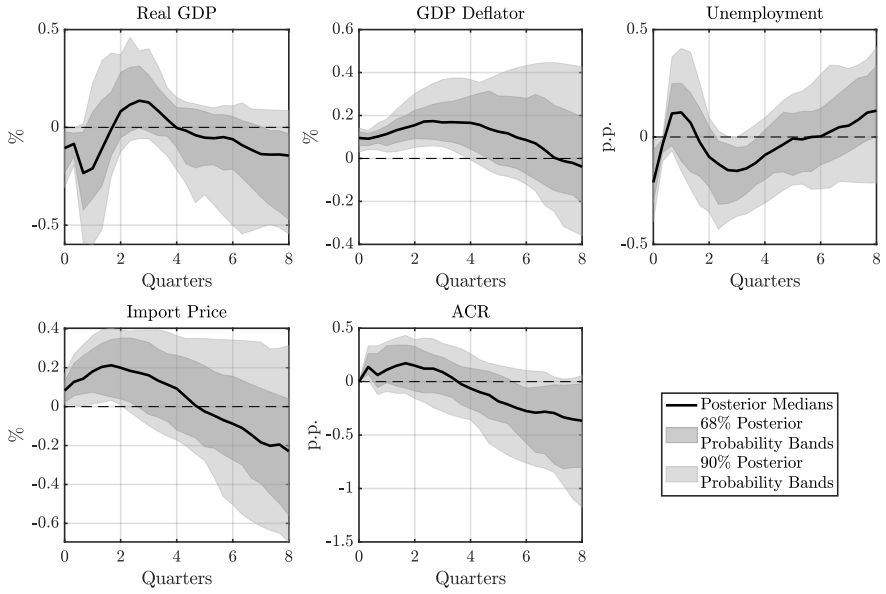



**Figure F.8:** IRFs to an Adverse Shock to Labor Supply: $k = 1, 2$

*Notes.* The IRFs to a one standard deviation adverse shock to labor supply are identified using a set of restrictions that are the same as Restrictions 1, 2, and 3, except that the sign restrictions on IRFs are imposed for longer horizons, i.e., $k = 1$ to $k = 1, 2$. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. The figure is based on 100,000 independent draws.

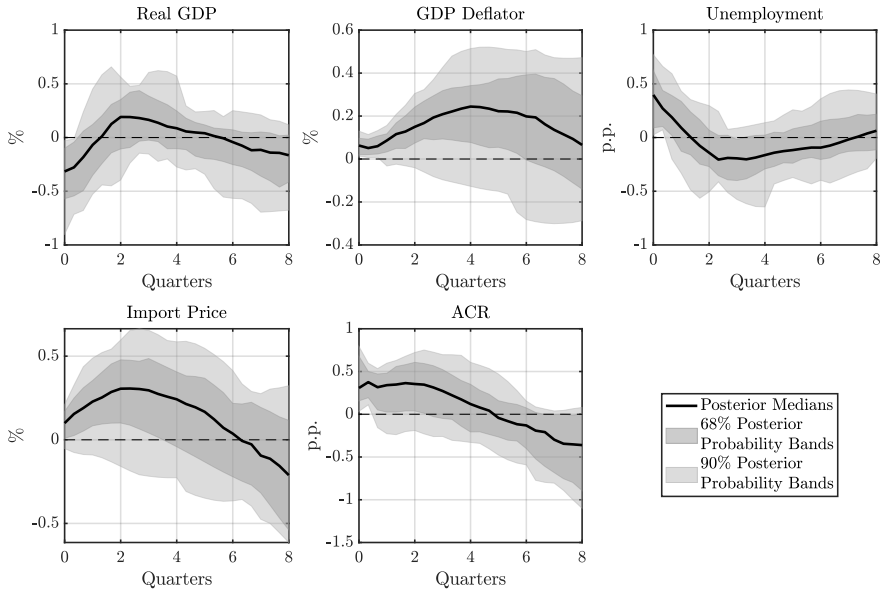



**Figure F.9:** IRFs to an Adverse Shock to Supply Chain: $k = 1, 2$

*Notes.* The IRFs to a one standard deviation adverse shock to supply chain are identified using a set of restrictions that are the same as Restrictions 1, 2, and 3, except that the sign restrictions on IRFs are imposed for longer horizons, i.e., $k = 1$ to $k = 1, 2$. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. The figure is based on 100,000 independent draws.

## F.2. No Zero Restrictions When Estimating with the GSCPI

As argued in the introduction and Section 4.2, the GSCPI index is not a pure supply chain disruption measure, as not only could the movements in its underlying data be driven by the demand-side factors (e.g., a high demand for tradable goods translates to a high shipping price), but also there is no differentiation between the supply-side factors (e.g., a rise in "delivery times" could originate from either a supply chain disruption or a labor shortage). As a result, the zero restrictions in Restrictions 1, 2, and 3 are no longer valid in the identification of the adverse shocks to aggregate demand and labor supply.[10]

Therefore, we conduct a robustness check by relaxing the zero restrictions when estimating the SVAR model with the GSCPI index included as an endogenous variable. Specifically, the identification restrictions are now the following:

10. Nevertheless, we still apply Restrictions 1, 2, and 3 in the identification of the structural shocks in Section 4.2 so as to control for any potential discrepancy that may arise due to differences in the identification restrictions.

**Restriction 1′.** ***An adverse shock to aggregate demand*** *leads to a negative response of real GDP, GDP deflator, and import price, as well as to a positive response of unemployment at* $k = 1$.

**Restriction 2′.** ***An adverse shock to labor supply*** *leads to a negative response of real GDP and unemployment, as well as to a positive response of GDP deflator and import price at* $k = 1$.

**Restriction 3′.** ***An adverse shock to supply chain*** *leads to a negative response of real GDP, as well as to a positive response of GDP deflator, unemployment, and GSCPI at* $k = 1$.

The estimation is still conducted using the Bayesian approach as in Arias, Rubio-Ramirez, and Waggoner (2018), Arias, Caldara, and Rubio-Ramírez (2019), and Arias et al. (2023). All the estimation specifications are kept the same as those applied in the baseline. As can be clearly seen in Figures F.10, F.11, and F.12, the biases of using the GSCPI index as a measure of global supply chain disruptions still persist.

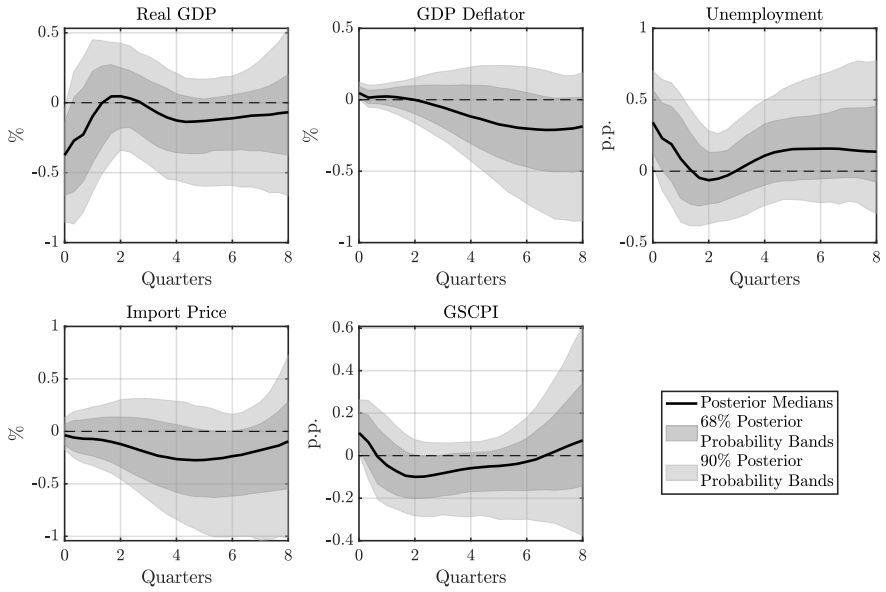



**Figure F.10:** IRFs to an Adverse Shock to Supply Chain: The GSCPI and Restrictions 1′, 2′, and 3′

*Notes.* The IRFs to a one standard deviation adverse shock to supply chain are identified using the GSCPI index and Restrictions 1′, 2′, and 3′. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. The figure is based on 100,000 independent draws.

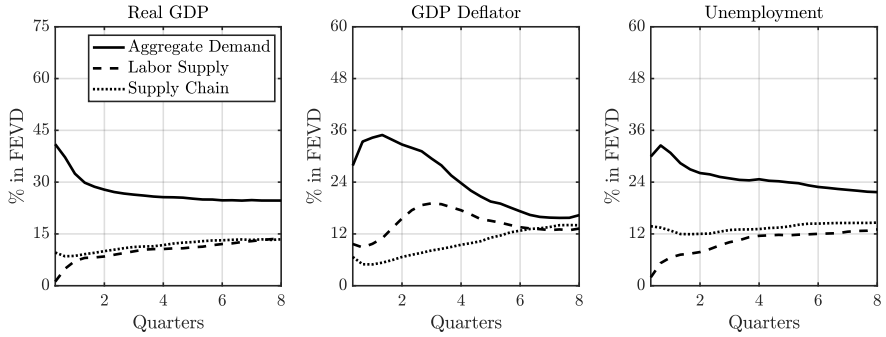



**Figure F.11:** FEVD from the SVAR: The GSCPI and Restrictions 1′, 2′, and 3′

*Notes.* Each line presents the median fraction of the forecast error variance for each endogenous variable, explained by each of the three identified structural shocks at various time horizons. The FEVD is estimated using the GSCPI index and Restrictions 1′, 2′, and 3′, and based on 100,000 independent draws.

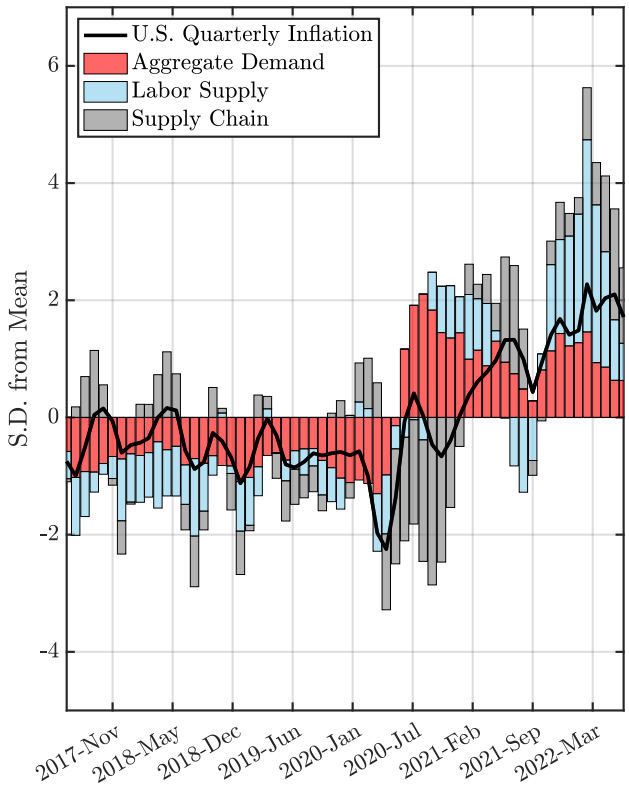



**Figure F.12:** HD of the GDP Deflator: The GSCPI and Restrictions 1′, 2′, and 3′

*Notes.* The solid line represents the standardized quarterly inflation rate in the U.S., i.e., Q-on-Q growth of the GDP deflator. The shaded bar represents the standardized cumulative historical contribution of each of the three structural shocks identified using the GSCPI index and Restrictions 1′, 2′, and 3′ to the U.S. inflation. The estimation results are obtained with each variable measured in percent change from the previous period, and are calculated based on 100,000 independent draws.

## F.3. The Fitted ACR

In this appendix, we conduct a robustness check of our baseline results by using a fitted ACR index in our estimation after regressing the port-specific ACR on the Oxford Stringency (OS) index (Mathieu et al. 2020) and port fixed effects.[11] Such a robustness check is intended to resolve the potential endogeneity concern regarding the ACR index when there are non-negligible changes in the container capacity between shipping routes that arise due to demand shifters which ultimately contribute to port congestion.

The OS index is essentially an indicator of mobility curtailment policies. Specifically, the authors of the OS index compile information on when and which measures governments take to contain the spread of the Covid-19 virus. The particular index we use is a simple average of nine individual component indicators, which measure the intensity of school closures, workplace closures, cancellation of public events, restrictions on public gatherings, closures of public transport, stay-at-home requirements, public information campaigns, restrictions on internal movements, and international travel controls, respectively. Since the OS index is dedicated to measuring the strictness of government policies, its variations are not subject to any demand-side factor. More importantly, strict containment policies enacted by local governments, as measured by a high value of the OS index, are expected to have contributed significantly to the escalation of port congestion worldwide, hence serving as the main cause of the global supply chain disruptions.[12] As such, the OS index could be applied as an instrument to the ACR index, and the resulting fitted ACR index could help us isolate the causal effects of global supply chain disruptions.

In the actual implementation, we first calculate the monthly average OS index for the country where each of the major container ports worldwide is located. In the process, we truncate our sample at 2020M1 as the OS index is only available after then. Subsequently, we regress the port-specific ACR on the corresponding OS index and port fixed effects, and

11. We thank Kun Wang for suggesting this robustness check.

12. The pandemic-related containment measures have put enormous strain on the global supply chain, disrupting the international shipping of tradable goods to the U.S. from around the world (Attinasi et al. 2021; Grimes and Edgecliffe-Johnson 2021; Dempsey 2022). For instance, lock-downs introduced to combat Covid-19 have limited the availability of workers to process cargo in ports as well as their work arrangements, leading to a slow-down of container processing, an escalation of port congestion, and hence a supply chain disruption cascading both upstream and downstream.

extract the fitted values, i.e., $\widehat{\text{ACR}}$. Lastly, we replace the ACR index with $\widehat{\text{ACR}}$ in our estimation. Once again, Restrictions 1, 2, and 3 are imposed on IRFs, and the estimation is undertaken using the Bayesian approach as in Arias, Rubio-Ramirez, and Waggoner (2018), Arias, Caldara, and Rubio-Ramírez (2019), and Arias et al. (2023). While all the other specifications are kept the same as those in the baseline, due to the reduced sample length, we include only one lag in the estimation and compute the IRFs and FEVD for only one year after impact to reduce parameter uncertainty.

As shown in Figures F.13 to F.15, the IRFs to each structural shock are quantitatively similar to those in Figures 9 to 11. At the same time, the FEVD in Figure F.16 is also comparable to that in Figure 13a.

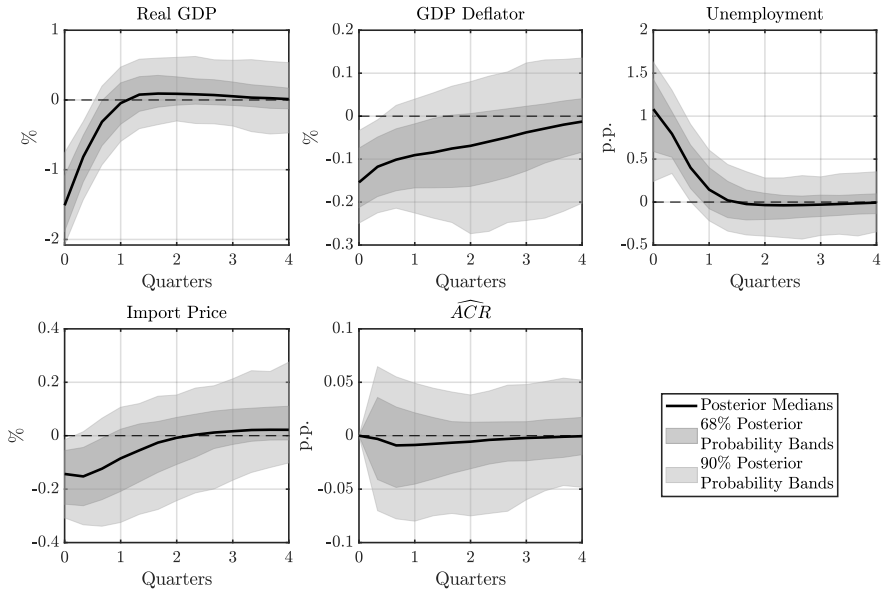



**Figure F.13:** IRFs to an Adverse Shock to Aggregate Demand: $\widehat{\text{ACR}}$ and Restrictions 1, 2, and 3

*Notes.* The IRFs to a one standard deviation adverse shock to aggregate demand are identified using $\widehat{\text{ACR}}$ and Restrictions 1, 2, and 3. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. The figure is based on 100,000 independent draws.

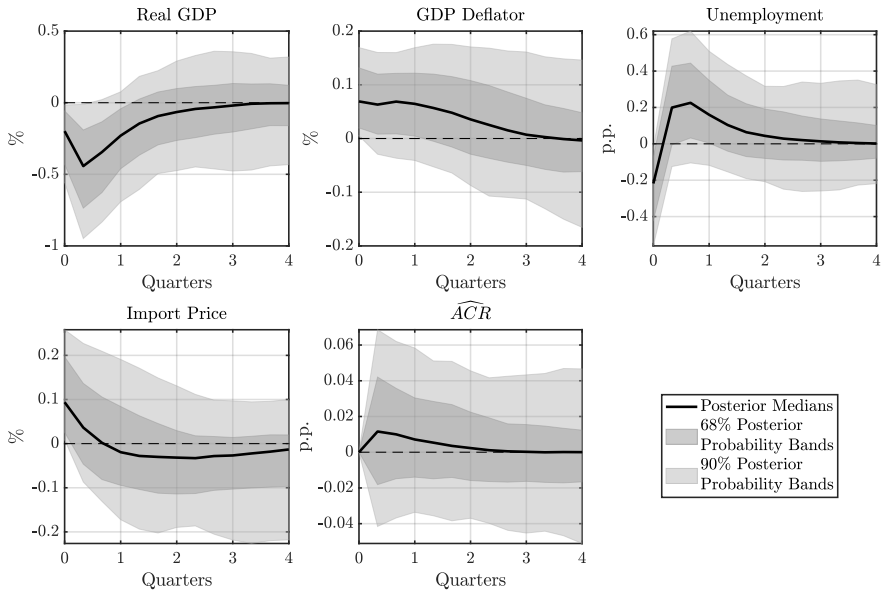



**Figure F.14:** IRFs to an Adverse Shock to Labor Supply: $\widehat{\text{ACR}}$ and Restrictions 1, 2, and 3

*Notes.* The IRFs to a one standard deviation adverse shock to labor supply are identified using $\widehat{\text{ACR}}$ and Restrictions 1, 2, and 3. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. The figure is based on 100,000 independent draws.

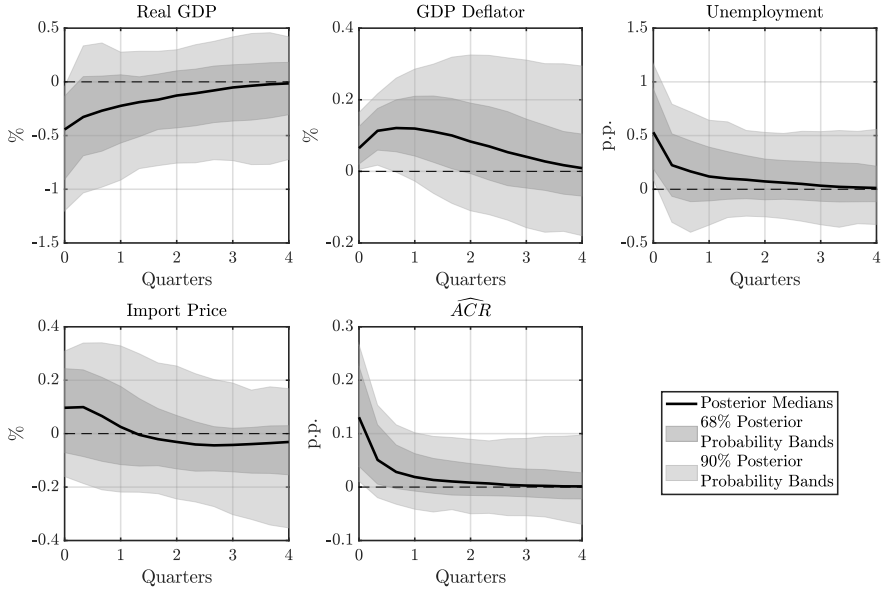



**Figure F.15:** IRFs to an Adverse Shock to Supply Chain: $\widehat{\text{ACR}}$ and Restrictions 1, 2, and 3

*Notes.* The IRFs to a one standard deviation adverse shock to supply chain are identified using $\widehat{\text{ACR}}$ and Restrictions 1, 2, and 3. The solid line shows the point-wise posterior medians, and the shaded bands represent the 68% and 90% equal-tailed point-wise posterior probability bands. The figure is based on 100,000 independent draws.

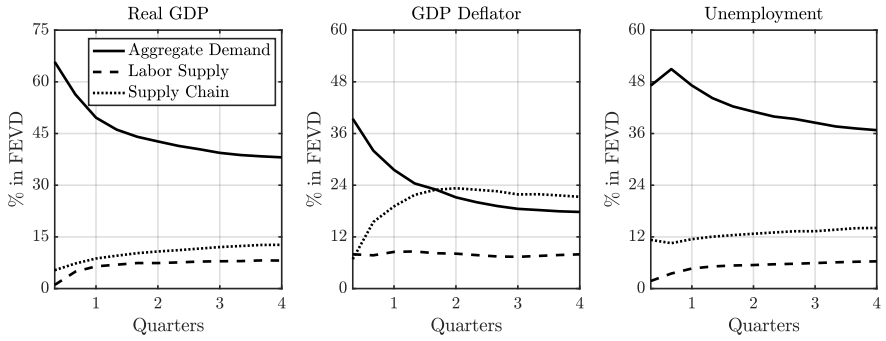



**Figure F.16:** FEVD from the SVAR: $\widehat{\text{ACR}}$ and Restrictions 1, 2, and 3

*Notes.* Each line presents the median fraction of the forecast error variance for each endogenous variable, explained by each of the three identified structural shocks at various time horizons. The FEVD is estimated using $\widehat{\text{ACR}}$ and Restrictions 1, 2, and 3, and based on 100,000 independent draws.

## F.4. Prior Robustness

Figures F.17, F.18, and F.19 show that the main conclusions from our baseline SVAR analysis are robust to using the prior robust approach for the SVARs proposed by Giacomini and Kitagawa (2021). Such an approach removes the need to specify the prior for the structural parameter given the reduced-form parameter, which is the component of the prior that is responsible for the asymptotic disagreement between Bayesian and frequentist inference. This is mainly achieved by constructing a class of priors that shares a single prior for the reduced-form parameter but allows for arbitrary conditional priors for the structural parameters given the reduced-form parameter.

In practice, we apply their Algorithm 1 to numerically approximate the set of posterior means and the associated robust credible regions for the IRFs of the selected endogenous variables to each structural shock. We make two modifications in the implementation of Algorithm 1. First, in Step 2 of Algorithm 1, to draw the orthonormal $Q$'s subject to Restrictions 1, 2, and 3, we apply the $QR$ decomposition method as in Arias, Rubio-Ramirez, and Waggoner (2018) instead of the original linear projection approach. These two ways of drawing $Q$ are comparable in terms of both the resulting distribution of $Q$ and computational cost. Second, we replace Step 3 of Algorithm 1 with Step 3′ of Algorithm 2 to approximate the lower and upper bounds of the prior robust posterior means, as well as those associated with the robust credible regions.

In Figures F.17, F.18, and F.19, the solid line shows the point-wise posterior medians, and the shaded area represents the 68% equal-tailed point-wise posterior probability bands. Their underlying data are from our baseline estimation outlined in Section 4.1. Alongside the posterior medians and probability bands, we plot the set of prior robust posterior means using dotted curves, and the corresponding 68% robust credible regions using dashed-dotted curves. Their underlying data are based on 1,000 independent draws of the reduced-form parameters and 100,000 orthogonal matrices draws for each reduced-form parameter.

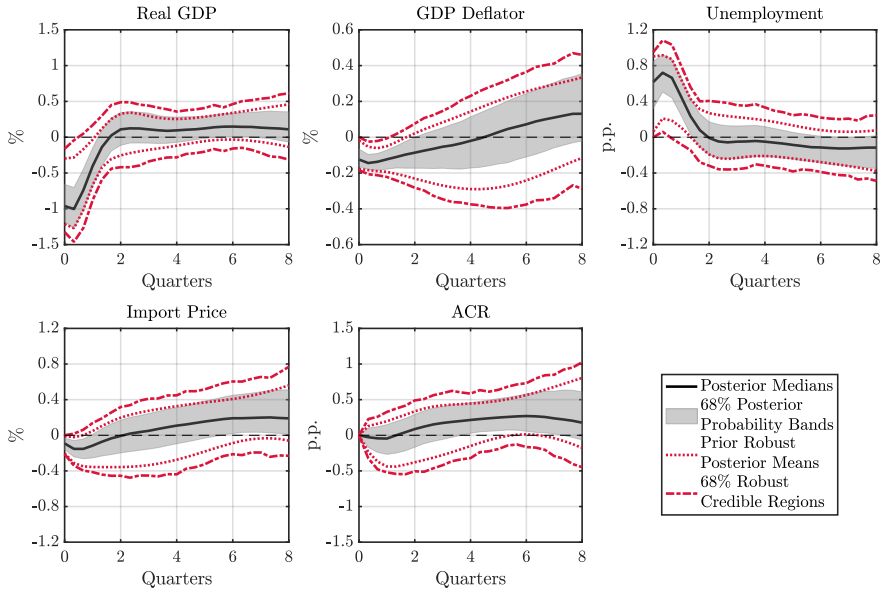



**Figure F.17:** IRFs to an Adverse Shock to Aggregate Demand Using the Prior Robust Approach in Giacomini and Kitagawa (2021)

*Notes.* The IRFs to a one standard deviation adverse shock to aggregate demand are estimated using the prior robust approach for the SVARs proposed by Giacomini and Kitagawa (2021). The solid line shows the point-wise posterior medians, and the shaded area represents the 68% equal-tailed point-wise posterior probability bands, which are based on the data from our baseline estimation outlined in Section 4.1. The dotted curves illustrate the set of prior robust posterior means, and the dashed-dotted curves depict the 68% robust credible regions. These curves are obtained from 1,000 independent draws of the reduced-form parameters and 100,000 orthogonal matrix draws for each reduced-form parameter.

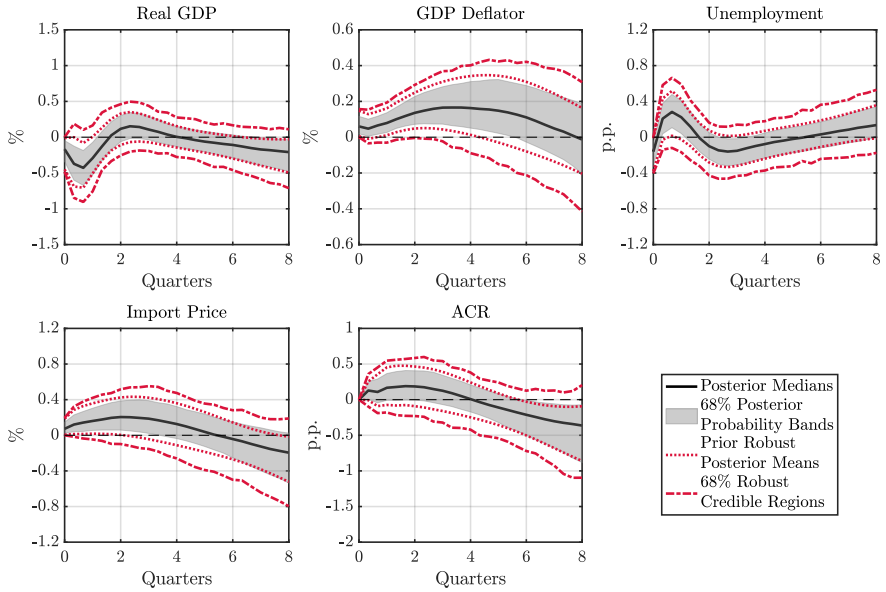



**Figure F.18:** IRFs to an Adverse Shock to Labor Supply Using the Prior Robust Approach in Giacomini and Kitagawa (2021)

*Notes.* The IRFs to a one standard deviation adverse shock to labor supply are estimated using the prior robust approach for the SVARs proposed by Giacomini and Kitagawa (2021). The solid line shows the point-wise posterior medians, and the shaded area represents the 68% equal-tailed point-wise posterior probability bands, which are based on the data from our baseline estimation outlined in Section 4.1. The dotted curves illustrate the set of prior robust posterior means, and the dashed-dotted curves depict the 68% robust credible regions. These curves are obtained from 1,000 independent draws of the reduced-form parameters and 100,000 orthogonal matrix draws for each reduced-form parameter.

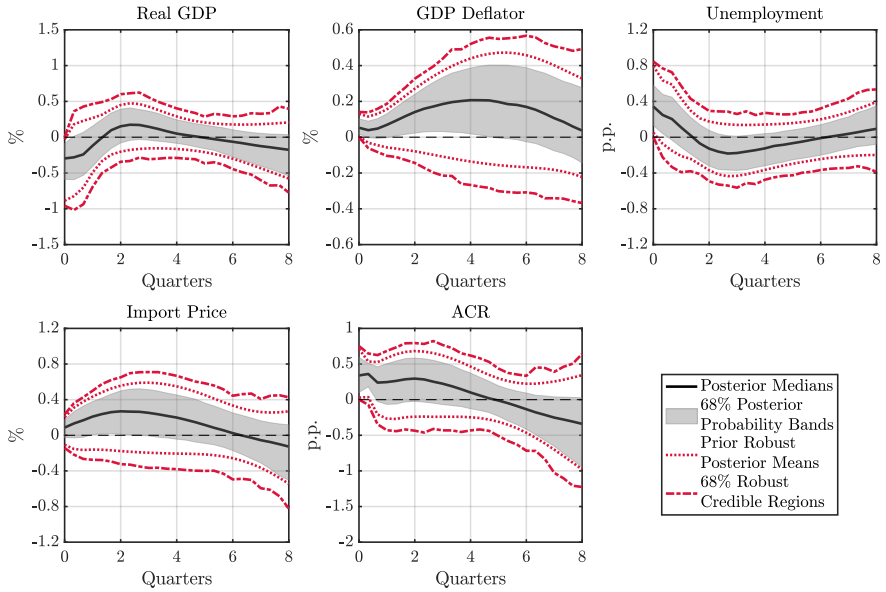



**Figure F.19:** IRFs to an Adverse Shock to Supply Chain Using the Prior Robust Approach in Giacomini and Kitagawa (2021)

*Notes.* The IRFs to a one standard deviation adverse shock to supply chain are estimated using the prior robust approach for the SVARs proposed by Giacomini and Kitagawa (2021). The solid line shows the point-wise posterior medians, and the shaded area represents the 68% equal-tailed point-wise posterior probability bands, which are based on the data from our baseline estimation outlined in Section 4.1. The dotted curves illustrate the set of prior robust posterior means, and the dashed-dotted curves depict the 68% robust credible regions. These curves are obtained from 1,000 independent draws of the reduced-form parameters and 100,000 orthogonal matrix draws for each reduced-form parameter.

# G. Priors and Identification in TVAR

## G.1. Priors

Our formulation of the prior in the TVAR model follows Bańbura, Giannone, and Reichlin (2010), Mumtaz and Zanetti (2012), and Pizzinelli, Theodoridis, and Zanetti (2020), and the same prior has been applied to the parameters in both the supply chain disrupted ($\mathbb{D}$) and undisrupted ($\mathbb{U}$) regimes. Specifically, we write the TVAR model in Equation (26) compactly as a system of multivariate regressions:

$$\boldsymbol{y} = (\boldsymbol{M}_{\mathbb{D}}\boldsymbol{x}_{\mathbb{D}} + \boldsymbol{u}_{\mathbb{D}})\boldsymbol{I} + (\boldsymbol{M}_{\mathbb{U}}\boldsymbol{x}_{\mathbb{U}} + \boldsymbol{u}_{\mathbb{U}})(\boldsymbol{1}_{T\times T} - \boldsymbol{I}), \tag{G.1}$$

where $\boldsymbol{y} = [\boldsymbol{y}_1 \ \dots \ \boldsymbol{y}_T]$ is an $n \times T$ matrix, $\boldsymbol{x}_{\mathbb{D}} = [\boldsymbol{x}_{\mathbb{D},1} \ \dots \ \boldsymbol{x}_{\mathbb{D},T}]$ is an $m \times T$ matrix with $\boldsymbol{x}_{\mathbb{D},t} = [\boldsymbol{y}'_{t-1} \ \dots \ \boldsymbol{y}'_{t-L} \ \boldsymbol{\omega}'_t]'$, $\boldsymbol{x}_{\mathbb{U}} = [\boldsymbol{x}_{\mathbb{U},1} \ \dots \ \boldsymbol{x}_{\mathbb{U},T}]$ is an $m \times T$ matrix with $\boldsymbol{x}_{\mathbb{U},t} = [\boldsymbol{y}'_{t-1} \ \dots \ \boldsymbol{y}'_{t-L} \ \boldsymbol{\omega}'_t]'$, $\boldsymbol{\omega}_t = [1, t]'$ is a $2 \times 1$ vector of a constant and a linear trend, $\boldsymbol{u}_{\mathbb{D}} = [\boldsymbol{\Sigma}_{\mathbb{D}}^{1/2}\boldsymbol{\epsilon}_1 \ \dots \ \boldsymbol{\Sigma}_{\mathbb{D}}^{1/2}\boldsymbol{\epsilon}_T]$ is an $n \times T$ matrix, $\boldsymbol{u}_{\mathbb{U}} = [\boldsymbol{\Sigma}_{\mathbb{U}}^{1/2}\boldsymbol{\epsilon}_1 \ \dots \ \boldsymbol{\Sigma}_{\mathbb{U}}^{1/2}\boldsymbol{\epsilon}_T]$ is an $n \times T$ matrix, $\boldsymbol{\Sigma}_{\mathbb{D}}$ and $\boldsymbol{\Sigma}_{\mathbb{U}}$ are the covariance matrices, $\boldsymbol{I} = diag[I_1 \ \dots \ I_T]$ is a $T \times T$ diagonal matrix, $\boldsymbol{M}_{\mathbb{D}} = [\boldsymbol{B}'_{\mathbb{D},1} \ \dots \ \boldsymbol{B}'_{\mathbb{D},L} \ \boldsymbol{C}'_{\mathbb{D}}]$ and $\boldsymbol{M}_{\mathbb{U}} = [\boldsymbol{B}'_{\mathbb{U},1} \ \dots \ \boldsymbol{B}'_{\mathbb{U},L} \ \boldsymbol{C}'_{\mathbb{U}}]$ are two $n \times m$ matrices containing the TVAR coefficients associated with each regime, and $m = nL + 2$. Given Equation (G.1), for each regime $r \in \{\mathbb{D}, \mathbb{U}\}$, we assume that the prior distribution of the parameter vector, $vec(\boldsymbol{M}_r)$, has a Normal-Inverse-Wishart conjugate form.[13] Such a form can be written as:

$$\begin{aligned} vec(\boldsymbol{M}_r)|\boldsymbol{\Sigma}_r &\sim N\Big(vec(\boldsymbol{M}_r^0), \boldsymbol{\Sigma}_r \otimes \boldsymbol{\Omega}_r^0\Big), \\ \boldsymbol{\Sigma}_r &\sim IW\Big(\boldsymbol{S}_r^0, \alpha_r^0\Big), \end{aligned} \tag{G.2}$$

where $vec(\boldsymbol{M}_r^0)$ is the prior mean of the parameter vector, $\boldsymbol{\Omega}_r^0$ controls the tightness around this prior, $\boldsymbol{S}_r^0$ is the prior scale matrix of the Inverse-Wishart ($IW$) distribution, and $\alpha_r^0$ denotes the prior degrees of freedom. Essentially, the prior in Equation (G.2) is a generalization of the Minnesota prior discussed in Litterman (1986) and assumes that the endogenous variables follow a random walk or an AR(1) process. This is based on the idea that recent lags provide more reliable information on the dynamics of the system and therefore the estima-

13. $vec(\cdot)$ denotes the operator that stacks the columns of a matrix into a vector.

tion should assign them a higher weighting. Unlike the original formulation in Litterman (1986) however, the prior in Equation (G.2) does not assume a diagonal, fixed, and known covariance matrix, making it more suitable for our structural analysis.

The Normal-Inverse-Wishart prior implies that, while the prior expectations and variances of the coefficient matrices for the constant and linear trend, $\boldsymbol{C}_r$, are diffuse, those associated with the autoregressive matrices, $\boldsymbol{B}_{r,l}$, can be written as:

$$\begin{aligned}\mathbb{E}[(\boldsymbol{B}_{r,l})_{i,j}] &= \begin{cases}\beta^0_{r,i}, & \text{if } i=j,\ l=1;\\ 0, & \text{otherwise;}\end{cases}\\ \mathbb{V}[(\boldsymbol{B}_{r,l})_{i,j}] &= \lambda\sigma_i^2/\sigma_j^2,\end{aligned} \tag{G.3}$$

where $\beta^0_{r,1},\ldots,\beta^0_{r,n}$ are the prior means of the autoregressive coefficients, $\sigma_1,\ldots,\sigma_n$ are the prior error standard deviations, and the hyper-parameter $\lambda$ controls the overall tightness of the prior distribution such that a larger $\lambda$ corresponds to a looser prior. As described in Bańbura, Giannone, and Reichlin (2010) and commonly used in the literature of Bayesian SVARs, the prior moments in Equation (G.3) can be implemented by adding $T_{r,d}$ dummy observations $\boldsymbol{y}_{r,d}$ and $\boldsymbol{x}_{r,d}$ to the system of regressions in Equation (G.1) that correspond to each regime, with $\boldsymbol{y}_{r,d}$ and $\boldsymbol{x}_{r,d}$ satisfying:

$$\boldsymbol{y}_{r,d} = \begin{bmatrix} diag[\beta^0_{r,1}\sigma_1 & \ldots & \beta^0_{r,n}\sigma_n]/\lambda \\ \mathbf{0}_{n(L-1)\times n} \\ diag[\sigma_1 & \ldots & \sigma_n] \\ \mathbf{0}_{2\times n}\end{bmatrix},\ \boldsymbol{x}_{r,d} = \begin{bmatrix} J_L \otimes diag[\sigma_1 & \ldots & \sigma_n]/\lambda & \mathbf{0}_{nL\times 1} & \mathbf{0}_{nL\times 1} \\ \mathbf{0}_{n\times nL} & & \mathbf{0}_{n\times 1} & \mathbf{0}_{n\times 1} \\ \mathbf{0}_{1\times nL} & & \xi & 0 \\ \mathbf{0}_{1\times nL} & & 0 & \xi\end{bmatrix},$$

where $J_L = diag[1 \quad \ldots \quad L]$ and the hyper-parameter $\xi$ controls the prior on the constant and the linear trend such that a small number makes the prior uninformative. Subsequently, the prior moments in Equation (G.2) are simply functions of $\boldsymbol{y}_{r,d}$ and $\boldsymbol{x}_{r,d}$, which are given by:

$$\begin{aligned}\boldsymbol{M}^0_r &= \boldsymbol{y}_{r,d}\boldsymbol{x}'_{r,d}(\boldsymbol{x}_{r,d}\boldsymbol{x}'_{r,d})^{-1},\\ \boldsymbol{\Omega}^0_r &= (\boldsymbol{x}_{r,d}\boldsymbol{x}'_{r,d})^{-1},\\ \boldsymbol{S}^0_r &= (\boldsymbol{y}_{r,d}-\boldsymbol{M}^0_r\boldsymbol{x}_{r,d})(\boldsymbol{y}_{r,d}-\boldsymbol{M}^0_r\boldsymbol{x}_{r,d})',\\ \alpha^0_r &= T_{r,d}-m.\end{aligned}$$

With the Normal-Inverse-Wishart prior being conjugate, the conditional posterior distribution of the parameter vector is also Normal-Inverse-Wishart (Bańbura, Giannone, and Reichlin 2010; Mumtaz and Zanetti 2012):

$$vec(\boldsymbol{M}_r)|\boldsymbol{\Sigma}_r, \boldsymbol{y} \sim N\Big(vec(\tilde{\boldsymbol{M}}_r), \boldsymbol{\Sigma}_r \otimes (\tilde{\boldsymbol{x}}_r \tilde{\boldsymbol{x}}_r')^{-1}\Big),$$
$$\boldsymbol{\Sigma}_r|\boldsymbol{y} \sim IW\Big(\tilde{\boldsymbol{S}}_r, T_{r,d} + 2 + T - m\Big),$$

where the parameters associated with the posterior are given by:

$$\tilde{\boldsymbol{M}}_r = \tilde{\boldsymbol{y}}_r \tilde{\boldsymbol{x}}_r' (\tilde{\boldsymbol{x}}_r \tilde{\boldsymbol{x}}_r')^{-1},$$
$$\tilde{\boldsymbol{S}}_r^0 = (\tilde{\boldsymbol{y}}_r - \tilde{\boldsymbol{M}}_r \tilde{\boldsymbol{x}}_r)(\tilde{\boldsymbol{y}}_r - \tilde{\boldsymbol{M}}_r \tilde{\boldsymbol{x}}_r)',$$

in which the terms $\tilde{\boldsymbol{y}}_r$ and $\tilde{\boldsymbol{x}}_r$ are the matrices of $\boldsymbol{y}_r$ and $\boldsymbol{x}_r$ augmented with the dummy observations $\boldsymbol{y}_{r,d}$ and $\boldsymbol{x}_{r,d}$ respectively.[14]

Following Mumtaz and Zanetti (2012) and Pizzinelli, Theodoridis, and Zanetti (2020), we obtain the values of the prior mean of each autoregressive coefficient, $\beta_{r,i}^0$, as well as the prior error standard deviation, $\sigma_i$, from the OLS estimation of a univariate AR(1) model for each endogenous variable. In addition, we set $\lambda = 0.25$ to ensure fast lag decay towards zero. Finally, in terms of the prior distribution of $\overline{ACR}$, we assume that it is normally distributed, with the mean set at the median of the ACR series and the standard deviation calibrated to deliver a Markov Chain Monte Carlo (MCMC) acceptance rate of approximately 70%.

## G.2. Identification Using the PFA

Following Uhlig (2005) and Mountford and Uhlig (2009), the identification scheme we employ in the study of the state-dependent effects of a contractionary monetary policy shock amounts to finding an impulse vector $a$ that minimizes a given criterion function $f(\cdot)$ on the space of all impulse vectors. This function penalizes positive impulse responses of real GDP, GDP deflator, and import price as well as negative impulse responses of the Federal Funds Rate and unemployment at horizons $k = 1, \ldots, K$, while satisfying the zero restriction imposed on the impulse response of ACR at horizon $k = 1$. The scheme is applied separately for the observations in each regime. Hence, for simplicity, we drop the regime-specific notation

14. $\boldsymbol{y}_r$ is the part of $\boldsymbol{y}$ that is associated with regime $r \in \{\mathbb{D}, \mathbb{U}\}$.

$r \in \{\mathbb{D}, \mathbb{U}\}$ in the following description.

The PFA is implemented numerically as follows. Define the penalty function as:

$$f(x) = \begin{cases} x, & \text{if } x \leq 0; \\ 100x, & \text{if } x > 0, \end{cases} \tag{G.4}$$

which penalizes positive responses in linear proportion and rewards negative responses in linear proportion, albeit at a slope 100 times smaller than the slope for penalties on the positive side. For the true VAR coefficients, let $r_{j,a}(k),\ k = 1, \ldots, K$ be the impulse response of variable $j$ and $\sigma_j$ be the standard deviation of the series for variable $j$. Let $\iota_j = -1$ if $j$ is the index of Federal Funds Rate or unemployment in the data vector, and $\iota_j = 1$ if $j$ is the index of real GDP, GDP deflator, or import price in the data vector. Define the contractionary monetary policy impulse vector as that impulse vector $a$, which minimizes the total penalty $\varphi(a)$ subject to the zero restriction imposed on the impulse response of the ACR index at horizon $k = 1$:

$$\varphi(a) = \sum_{j \in \left\{ \begin{array}{c} \text{“Federal Funds Rate”}, \\ \text{“real GDP”}, \\ \text{“GDP deflator”}, \\ \text{“unemployment”}, \\ \text{“import price”} \end{array} \right\}} \Big[ \sum_{k=1}^{K} f\Big( \iota_j \frac{r_{j,a}(k)}{\sigma_j} \Big) \Big].$$

The re-scaling by $\sigma_j$ is necessary to make the deviations across different impulse responses comparable to each other. Note that the sign of the penalty direction is flipped for the Federal Funds Rate and unemployment. Since the true VAR is unknown, we find the contractionary monetary policy vector for each draw from the posterior. Such a step involves numerical minimization, and we keep all the draws and accordingly calculate all the corresponding impulse vectors. As a result, the IRFs in the main text are calculated based on these.

## G.3. Posterior and Identified Regimes

The posterior distribution of the threshold $\overline{ACR}$ is plotted in Figure G.1, while the time series of the identified regimes using the median of such a posterior is plotted in Figure G.2.

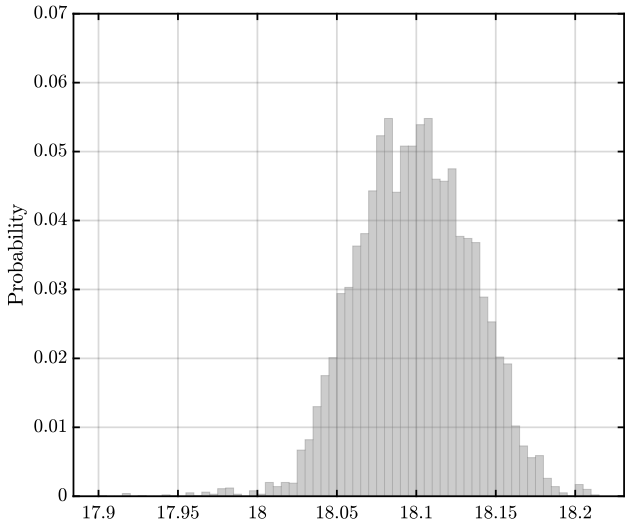



**Figure G.1:** Posterior Distribution of the Threshold $\overline{ACR}$

*Notes.* The figure plots the posterior distribution of the ACR threshold value, i.e., $\overline{ACR}$, based on 10,000 independent draws.

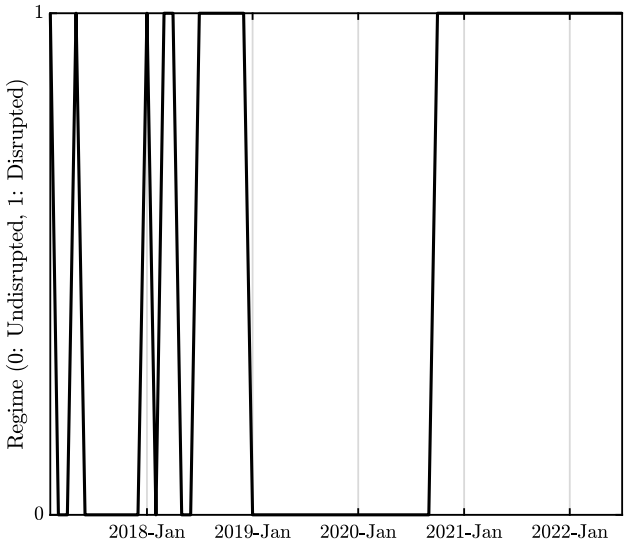



**Figure G.2:** Regimes Based on the Median of the Posterior $\overline{ACR}$

*Notes.* The solid line, switching from zero to one, represents the current regime as identified by the median of the posterior distribution of the ACR threshold, i.e., $median(\overline{ACR}) = 18.0990$. The value of one corresponds to the supply chain disrupted ($\mathbb{D}$) regime, while the value of zero corresponds to the supply chain undisrupted ($\mathbb{U}$) regime.

# H. Robustness of TVAR Results

In Figures H.1 and H.2, we show that our state-dependence results are robust to considering different lag structures in the TVAR model, i.e., two or three lags. We do not consider four lags or beyond due to parameter uncertainty resulting from our limited sample length. We also show in Figure H.3 that the results are robust when a looser prior is undertaken in the estimation, i.e., $\lambda = 0.5$. Furthermore, we extend the horizons at which we impose the sign restrictions – i.e., from $k = 1$ to $k = 1, 2, 3$ – so as to put more disciplines on the behaviors of IRFs. As shown in Figure H.4, once again, our benchmark results still hold.

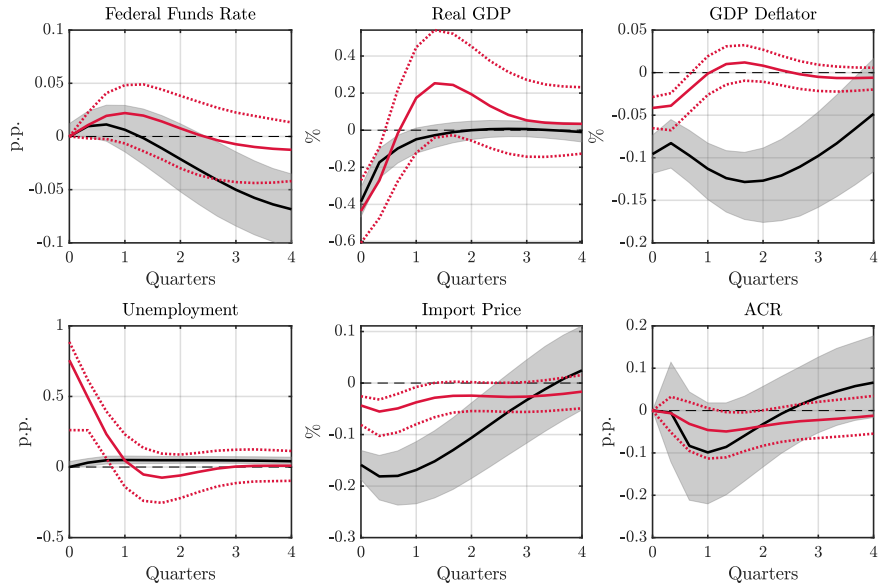



**Figure H.1:** State-Dependent Effects of a Contractionary Monetary Policy Shock: $L = 2$

*Notes.* The figure shows the IRFs to a one standard deviation contractionary monetary policy shock identified using a TVAR specification as in Equation (26) with two lags, as well as Restriction 4, for both the supply chain disrupted and undisrupted regimes. The black solid (red solid) line shows the point-wise posterior medians, and the black shaded area (red dotted lines) depicts the 68% equal-tailed point-wise posterior probability bands for the supply chain disrupted (undisrupted) regime. The figure is based on 10,000 independent draws from the posterior.

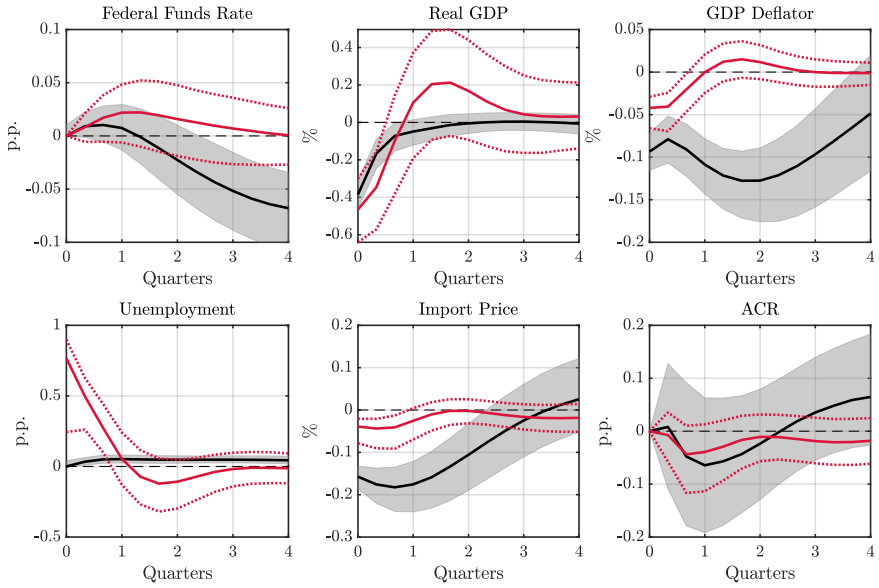



**Figure H.2:** State-Dependent Effects of a Contractionary Monetary Policy Shock: $L = 3$

*Notes.* The figure shows the IRFs to a one standard deviation contractionary monetary policy shock identified using a TVAR specification as in Equation (26) with three lags, as well as Restriction 4, for both the supply chain disrupted and undisrupted regimes. The black solid (red solid) line shows the point-wise posterior medians, and the black shaded area (red dotted lines) depicts the 68% equal-tailed point-wise posterior probability bands for the supply chain disrupted (undisrupted) regime. The figure is based on 10,000 independent draws from the posterior.

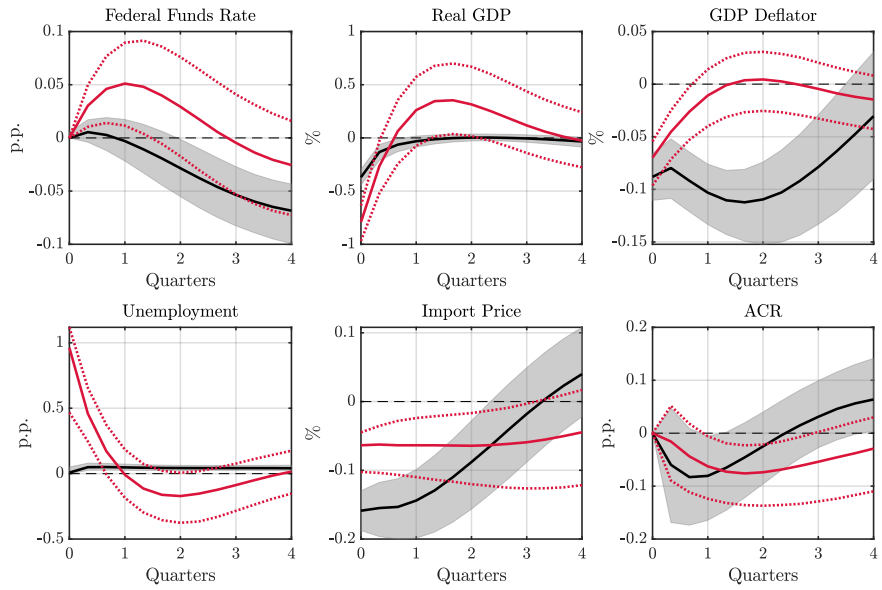



**Figure H.3:** State-Dependent Effects of a Contractionary Monetary Policy Shock: $\lambda = 0.5$

*Notes.* The figure shows the IRFs to a one standard deviation contractionary monetary policy shock identified using a TVAR specification as in Equation (26) with $\lambda = 0.5$, as well as Restriction 4, for both the supply chain disrupted and undisrupted regimes. The black solid (red solid) line shows the point-wise posterior medians, and the black shaded area (red dotted lines) depicts the 68% equal-tailed point-wise posterior probability bands for the supply chain disrupted (undisrupted) regime. The figure is based on 10,000 independent draws from the posterior.

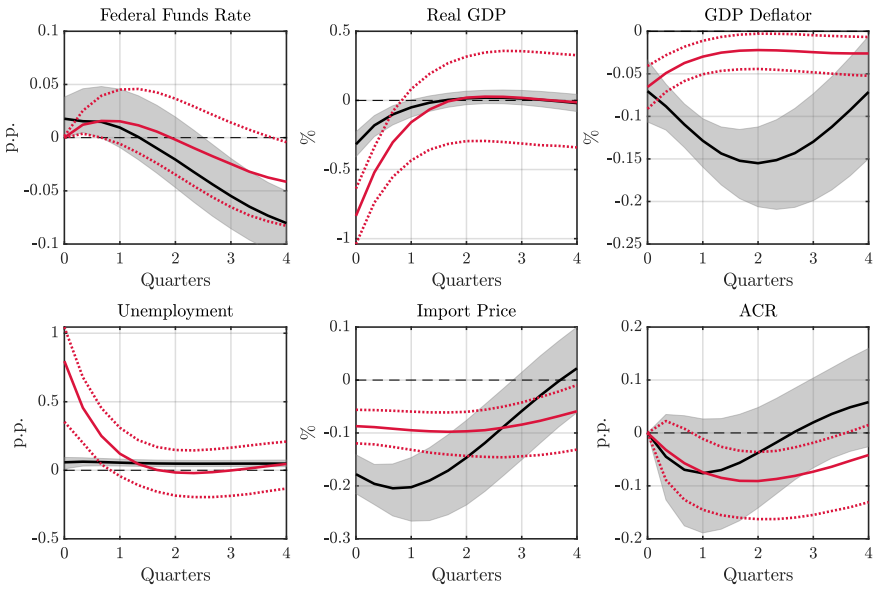



**Figure H.4:** State-Dependent Effects of a Contractionary Monetary Policy Shock: $k = 1, 2, 3$

*Notes.* The figure shows the IRFs to a one standard deviation contractionary monetary policy shock identified using Restriction 4 for both the supply chain disrupted and undisrupted regimes. Restriction 4 is imposed for longer horizons, i.e., $k = 1, 2, 3$. The black solid (red solid) line shows the point-wise posterior medians, and the black shaded area (red dotted lines) depicts the 68% equal-tailed point-wise posterior probability bands for the supply chain disrupted (undisrupted) regime. The figure is based on 10,000 independent draws from the posterior.

# I. State-Dependence Results Using the LPs

In this appendix, as a robustness check to our state-dependence results obtained using the TVAR model, we work with LPs to identify a contractionary monetary policy shock and analyze how it affects the macro aggregates for the U.S. economy depending on the level of global supply chain disruptions. LPs are a flexible approach that allows us to address the state-dependence of monetary policy without making strong parametric assumptions. Specifically, we use the LPs with interaction terms as in Ramey and Zubairy (2018), and our identification scheme consists of sign restrictions implemented as described in Plagborg-Møller and Wolf (2021). Consider the following $n \times (K+1)$ projections:

$$\begin{aligned} y_{i,t+k} =& I_t \left[ \boldsymbol{\beta}'_{\mathbb{D},i,k,0} \boldsymbol{y}_t + \sum_{l=1}^{L} \boldsymbol{\beta}'_{\mathbb{D},i,k,l} \boldsymbol{y}_{t-l} + \boldsymbol{C}'_{\mathbb{D},i,k} \boldsymbol{\omega}_t \right] \\ &+ (1 - I_t) \left[ \boldsymbol{\beta}'_{\mathbb{U},i,k,0} \boldsymbol{y}_t + \sum_{l=1}^{L} \boldsymbol{\beta}'_{\mathbb{U},i,k,l} \boldsymbol{y}_{t-l} + \boldsymbol{C}'_{\mathbb{U},i,k} \boldsymbol{\omega}_t \right] + u_{i,k,t}, \end{aligned} \tag{I.1}$$

where $1 \leq i \leq n$, $0 \leq k \leq K$, $\boldsymbol{y}_t$ is an $n \times 1$ vector of the same endogenous variables as in Section 5.2 save for the ACR index (since it is the variable we use to split the sample), $y_{i,t+k}$ is the value of the $i$-th variable in $\boldsymbol{y}_{t+k}$, $\boldsymbol{\omega}_t = [1, t]'$ is a $2 \times 1$ vector of a constant and a linear trend, and $u_{i,k,t}$ is the reduced-form error corresponding to the $i$-th variable. The vector of the reduced-form errors for $k = 1$, $\boldsymbol{u}_{1,t} = [u_{1,1,t} \ \ \dots \ \ u_{n,1,t}]'$, is assumed to have mean zero and covariance matrix equal to $\mathbb{E}(\boldsymbol{u}_{1,t}\boldsymbol{u}'_{1,t}) = \boldsymbol{\Sigma}$.

Similar to the setup in the TVAR model, $I_t$ is a dummy variable that indicates whether the supply chain is disrupted. The supply chain disrupted regime is determined based on whether the one-month lag of the ACR index is above its median level over the sample. Figure I.1 shows the times series of the ACR index along with its 50th and 60th percentiles. As seen, there were frequent switches between the supply chain disrupted and undisrupted regimes before 2019. Subsequently, from early-2019 to mid-2020, the ACR index was constantly below its sample median. Such a pattern was reversed from mid-2020 onwards, as the ACR index started to climb up and the U.S. economy stepped into the disrupted regime. Note that the switches between the two regimes shown in Figure I.1 are almost identical to those

illustrated in Figure G.2 when the threshold $\overline{ACR}$ is determined endogenously in the TVAR estimation.

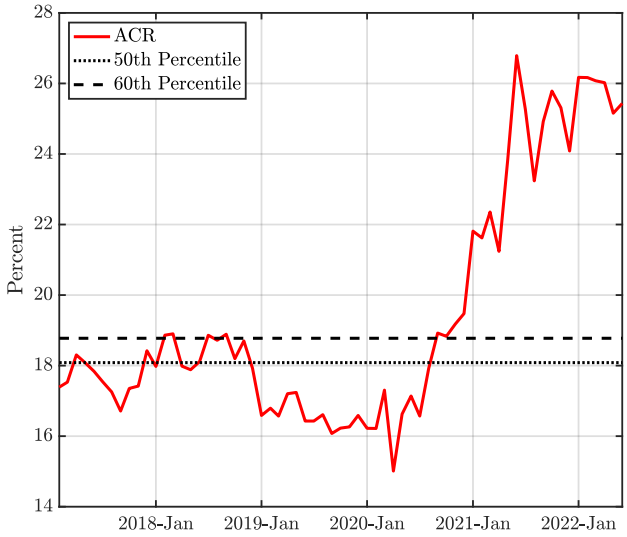



**Figure I.1:** ACR and Its 50th and 60th Percentiles

*Notes.* The figure plots the ACR index as well as its 50th and 60th percentiles during the sampling period from January 2017 to July 2022. The ACR index is computed using the AIS data of containerships and the IMA-DBSCAN algorithm developed in Appendix A. The index is presented in percentage terms and has been seasonally adjusted.

With the two regimes defined, the parameters $\boldsymbol{\beta}_{\mathbb{D},i,k,0}$, $\boldsymbol{\beta}_{\mathbb{D},i,k,l}$, and $\boldsymbol{C}_{\mathbb{D},i,k}$ correspond to the supply chain disrupted regime ($\mathbb{D}$), while the parameters $\boldsymbol{\beta}_{\mathbb{U},i,k,0}$, $\boldsymbol{\beta}_{\mathbb{U},i,k,l}$, and $\boldsymbol{C}_{\mathbb{U},i,k}$ correspond to the supply chain undisrupted regime ($\mathbb{U}$). Considering our limited sample length, we include only two lags in the estimation so as to reduce parameter uncertainty.

In order to identify a contractionary monetary policy shock, we follow our theoretical prediction in Proposition 6 and come up with an identification scheme similar to that in Section 5.2. Yet, since the ACR is not included in the estimation, we drop the zero restriction in Restriction 4 and re-write it as the following:

**Restriction 4′.** ***A contractionary monetary policy shock*** *leads to a negative response of real GDP, GDP deflator, and import price, as well as to a positive response of unemployment and Federal Funds Rate at* $k = 1, 2, 3$. *In addition, the on-impact response of GDP deflator in p.p. is bounded to be smaller than that of Federal Funds Rate in p.p.*

Note that Restriction 4′ is similar to Restriction 4, except that we impose restrictions on

the subsequent horizons to sharpen our identification, and an elasticity bound is imposed to discipline the identified set of IRFs corresponding to the GDP deflator. The latter variation is critical to ensure that our estimation is plausible, as in the absence of such a bound, the identified set would include a decline in the GDP deflator of 100 p.p. as being equally likely as a decline in the GDP deflator of 1 p.p. following an unexpected increase in the Federal Funds Rate of 0.05 p.p. Hence, we use a bound to rule out dubious IRFs following Kilian and Murphy (2012), Arias, Caldara, and Rubio-Ramírez (2019), and Arias et al. (2023).

With Restriction 4′, we compute the identified set of IRFs in each regime by numerically solving the quadratic program described in the supplement to Plagborg-Møller and Wolf (2021) using Algorithm 2 of Giacomini and Kitagawa (2021). Without loss of generality, we normalize the first shock to be the shock of interest. Let $\boldsymbol{S}$ denote a $15 \times n$ matrix that selects the IRFs which we restrict to be either positive or negative (there are in total 15 sign restrictions in Restriction 4′). Then, for each regime, we draw $D = 100,000$ orthogonal matrices $\boldsymbol{Q}_{r,d}$ (i.e., $\boldsymbol{Q}'_{r,d}\boldsymbol{Q}_{r,d} = \boldsymbol{Q}_{r,d}\boldsymbol{Q}'_{r,d} = \mathbf{1}_{n\times n}$) that satisfy the following:

$$\begin{aligned} \boldsymbol{S}\hat{\boldsymbol{B}}_{r,0:2}\hat{\boldsymbol{\Omega}}\boldsymbol{Q}_{r,d}\boldsymbol{e}_1 &\geq 0, \\ \frac{\boldsymbol{e}_3'\hat{\boldsymbol{B}}_{r,0}\hat{\boldsymbol{\Omega}}\boldsymbol{Q}_{r,d}\boldsymbol{e}_1}{\boldsymbol{e}_1'\hat{\boldsymbol{B}}_{r,0}\hat{\boldsymbol{\Omega}}\boldsymbol{Q}_{r,d}\boldsymbol{e}_1} + 1 &\geq 0, \end{aligned} \tag{I.2}$$

where $r \in \{\mathbb{D}, \mathbb{U}\}$, $1 \leq d \leq D$, $\hat{\boldsymbol{B}}_{r,0:2} = [\hat{\boldsymbol{B}}'_{r,0} \;\; \hat{\boldsymbol{B}}'_{r,1} \;\; \hat{\boldsymbol{B}}'_{r,2}]'$, $\hat{\boldsymbol{B}}_{r,k} = [\hat{\boldsymbol{\beta}}_{r,1,k,0} \;\; \dots \;\; \hat{\boldsymbol{\beta}}_{r,n,k,0}]'$, $\hat{\boldsymbol{\beta}}_{r,i,k,0}$ is the OLS estimate of $\boldsymbol{\beta}_{r,i,k,0}$, $\hat{\boldsymbol{\Omega}} = chol(\hat{\boldsymbol{\Sigma}})'$, $chol$ is the upper triangular Cholesky decomposition of $\hat{\boldsymbol{\Sigma}}$, and $\hat{\boldsymbol{\Sigma}}$ is the OLS estimate of $\boldsymbol{\Sigma}$.[15] Given that the entry $(i, j)$ in $\hat{\boldsymbol{B}}_{r,k}\hat{\boldsymbol{\Omega}}\boldsymbol{Q}_{r,d}$ gives the response of the $i$-th variable to the $j$-th shock at horizon $k$, the first inequality condition in Equation (I.2) summarizes all the sign restrictions imposed on IRFs, while the second inequality condition contains the elasticity bound, as $(\boldsymbol{e}_3'\hat{\boldsymbol{B}}_{r,0}\hat{\boldsymbol{\Omega}}\boldsymbol{Q}_{r,d}\boldsymbol{e}_1)/(\boldsymbol{e}_1'\hat{\boldsymbol{B}}_{r,0}\hat{\boldsymbol{\Omega}}\boldsymbol{Q}_{r,d}\boldsymbol{e}_1)$ denotes the ratio between the on-impact responses of the GDP deflator and the Federal Funds Rate, where $e_i$ is the $i$-th column of the $n$-dimensional identity matrix.

Given $\hat{\boldsymbol{B}}_{r,k}$ and $\hat{\boldsymbol{\Omega}}$, let $\{\boldsymbol{Q}_{r,d}\}_{d=1,\dots,D}$ be the draws that satisfy the restrictions in Equation

15. Vector inequalities are to be understood element-wise.

(I.2). The identified set of IRFs of the $i$-th variable at horizon $k$ is thus given by:

$$\left[\min_{d}\left\{0.05\frac{\boldsymbol{e}_i'\hat{\boldsymbol{B}}_{r,k}\hat{\boldsymbol{\Omega}}\boldsymbol{Q}_{r,d}\boldsymbol{e}_1}{\boldsymbol{e}_1'\hat{\boldsymbol{B}}_{r,0}\hat{\boldsymbol{\Omega}}\boldsymbol{Q}_{r,d}\boldsymbol{e}_1}\right\}_{d=1,\ldots,D},\ \max_{d}\left\{0.05\frac{\boldsymbol{e}_i'\hat{\boldsymbol{B}}_{r,k}\hat{\boldsymbol{\Omega}}\boldsymbol{Q}_{r,d}\boldsymbol{e}_1}{\boldsymbol{e}_1'\hat{\boldsymbol{B}}_{r,0}\hat{\boldsymbol{\Omega}}\boldsymbol{Q}_{r,d}\boldsymbol{e}_1}\right\}_{d=1,\ldots,D}\right], \tag{I.3}$$

where the factor $0.05/(\boldsymbol{e}_1'\hat{\boldsymbol{B}}_{r,0}\hat{\boldsymbol{\Omega}}\boldsymbol{Q}_{r,d}\boldsymbol{e}_1)$ is a normalization so that in both regimes, the contractionary monetary policy shock raises the Federal Funds Rate by 0.05 p.p. on impact.

Figure I.2 plots the point-wise medians and 68% equal-tailed point-wise probability bands associated with the identified set of IRFs in each regime following a contractionary monetary policy shock. We show the IRFs from horizon $k = 0$ up to horizon $k = 6$. The shorter horizon relative to the horizon of the IRFs shown in the TVAR model (Figure 16) is due to parameter uncertainty associated with the LPs. Nevertheless, as clearly seen in Figure I.2, the state-dependent effects of a contractionary monetary policy shock are still observable, as the responses of real GDP and unemployment are weaker while those of the GDP deflator and import price are stronger when the global supply chain is disrupted (i.e., $ACR_{t-1} > 18.1\%$, which is the sample median of the ACR index).

As a robustness check, we also consider a threshold at the 60th percentile of the ACR index (i.e., 18.8%) to distinguish between the supply chain disrupted and undisrupted regimes. As shown in Figure I.3, the main results are robust. We do not consider thresholds higher than the 60th percentile because, as shown in Figure I.1, they would imply a sharp division of our sample at around mid-2020, which may lead to a biased result.

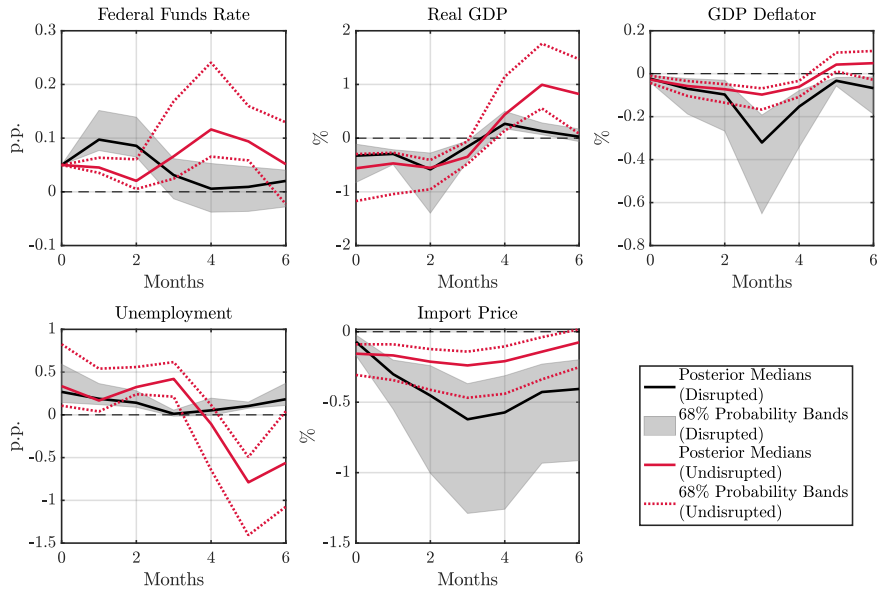



**Figure I.2:** State-Dependent Effects of a Contractionary Monetary Policy Shock: Using LPs With Interaction Terms and a Threshold at the Median of the ACR Index

*Notes.* The figure shows the IRFs to a contractionary monetary policy shock identified using LPs with interaction terms, as in Ramey and Zubairy (2018), along with Restriction 4′, for both the supply chain disrupted and undisrupted regimes. A threshold at the sample median of the ACR index (i.e., 18.1%) is applied to distinguish between the two regimes. The black solid (red solid) line shows the point-wise medians, and the black shaded area (red dotted lines) depicts the 68% equal-tailed point-wise probability bands for the supply chain disrupted (undisrupted) regime. The figure is based on 100,000 draws of orthogonal matrices.

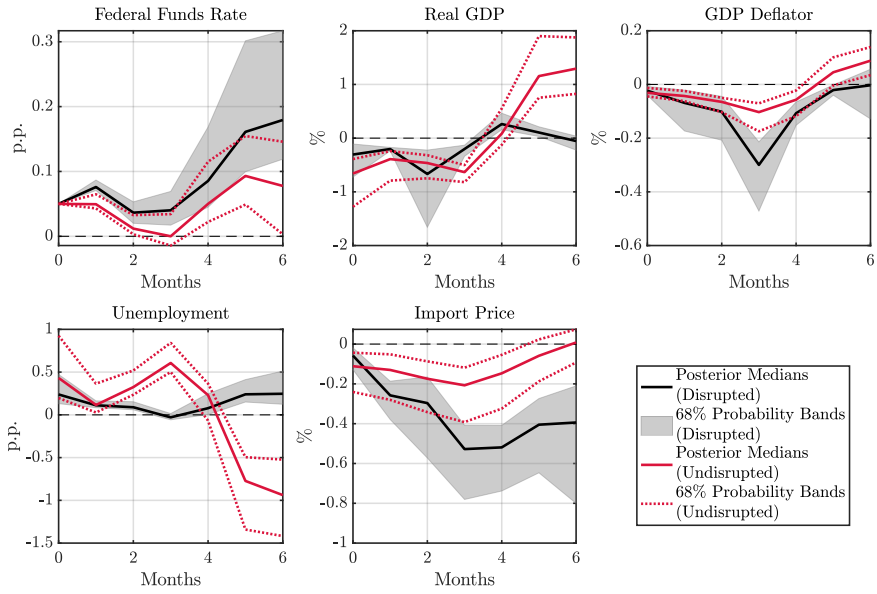



**Figure I.3:** State-Dependent Effects of a Contractionary Monetary Policy Shock: Using LPs With Interaction Terms and a Threshold at the 60th Percentile of the ACR Index

*Notes.* The figure shows the IRFs to a contractionary monetary policy shock identified using LPs with interaction terms, as in Ramey and Zubairy (2018), along with Restriction 4′, for both the supply chain disrupted and undisrupted regimes. A threshold at the 60th percentile of the ACR index (i.e., 18.8%) is applied to distinguish between the two regimes. The black solid (red solid) line shows the point-wise medians, and the black shaded area (red dotted lines) depicts the 68% equal-tailed point-wise probability bands for the supply chain disrupted (undisrupted) regime. The figure is based on 100,000 draws of orthogonal matrices.