Global Supply Chain Disruptions, Commodity Price Shocks and Macroeconomic Fluctuations in Japan*

Rui WANG[†]

Faculty of Economics, Rissho University[‡]

May 15, 2024

Abstract

In recent years, the concurrent occurrences of the COVID-19 pandemic and the Russian invasion of Ukraine have led to global disruptions in supply chains and a surge in commodity prices. Major advanced economies have experienced an increase in inflation rates and a decline in economic activity. Against this economic backdrop, this paper aims to address the strained condition of supply chains by employing the Global Supply Chain Pressure Index (GSCPI) alongside commodity price indices. Furthermore, it seeks to examine how fluctuations in these variables affect Japan's macroeconomic activities through local projection and structural VAR. In the local projection analysis, it has been observed that the strain on supply chains induces sustained increases in consumer and producer prices, further contributing to long-term declines in GDP and consumption. Within the structural VAR model framework, the identification of structural shocks is conducted through sign restrictions, affirming the significance of supply chain shocks and energy and food price shocks as crucial factors contributing to recent price increases. This confirmation is supported by variance decomposition and historical decomposition analyses.

Key Word: Supply Chain Disruptions; Energy Price; Food Price; Inflation; Local Projection; Structural VAR; Sign Restrictions;

JEL classification: E32; E37; F47; F62;

1 Introduction

Since January 2020, the global spread of the novel coronavirus disease (COVID-19) has significantly impacted economic activities worldwide. In major advanced economies, at the onset of the pandemic in 2020, there was a substantial decline in demand, leading to a temporary deflationary trend. However, starting from 2021, as the infection situation began to stabilize to some extent, economic activities gradually resumed, leading to a recovery in demand and subsequently pushing prices upward. In China, often referred to as the "world's factory", stringent

*The latest version of this paper can be downloaded from https://drive.google.com/drive/folders/1GcPQLLh5bXJtKqAkEONWYbxHFNcUmN6A?usp=share_link.

[†]Associate Professor at Faculty of Economics, Rissho University, Japan. E-mail: wangrui@ris.ac.jp

[‡]*4-2-16, Osaki, Shinagawa ward, Tokyo, 141-8602, Japan.*

COVID-19 measures were implemented nationwide until the end of 2022, causing disruptions in production and logistics that reverberated across the globe. Moreover, since February 2022, the Russian invasion of Ukraine has commenced, resulting in a surge in prices of commodities such as energy and food. Thus, the simultaneous occurrence of the COVID-19 pandemic and the Russian invasion of Ukraine has led to global disruptions in food and energy prices and the global supply chain. The increase in energy prices has led to higher transportation costs, further exacerbating strain on the supply chain.

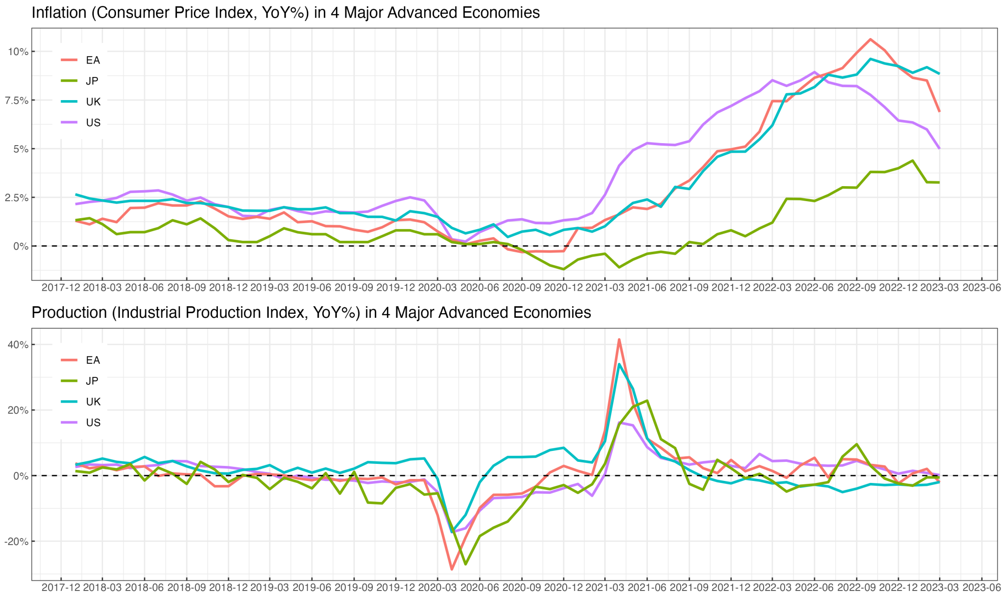


Figure 1: Inflation and Production in 4 Major Advanced Economies

Figure 1 illustrates the trends in inflation and production from January 2018 to March 2023 in 4 major advanced economies. As evident from Figure 1, since 2021, major advanced economies have recorded historically high inflation rates, significantly exceeding the central banks' price stability target of around 2%. In Japan, the prolonged ultra-low interest rate policy has widened the interest rate differential between Japan and the United States, leading to a depreciation of the yen and accelerating domestic price increases in the form of imported goods inflation. Anticipating rising production costs, many producers have preemptively increased prices, leading to what is commonly referred to as a "price hike rush".

In order to quantitatively assess the strain on the supply chain due to factors such as production and logistics stagnation and rising transportation costs, Benigno et al. (2022) have constructed an index called the Global Supply Chain Pressure Index (GSCPI), which is publicly released through the Federal Reserve Bank of New York[1]. This index is constructed by statistically processing two indicators representing shipping costs[2], four indicators represent-

[1]The latest data can be obtained from the website of the Federal Reserve Bank of New York (https://www.newyorkfed.org/research/policy/gscpi#/overview).

[2]The Baltic Dry Index (BDI) records the shipping costs of raw materials such as coal and steel, while the Harpex Index (HARPER PETERSEN Charter Rates Index) represents the transportation costs of container ships.

ing air freight costs[3], and three types of Purchasing Managers' Index (PMI) data[4] from seven countries/regions[5]. While the detailed methodology and source data of GSCPI are outlined in Benigno et al. (2022), it is worth noting that this index differs from conventional similar indicators in two aspects. Firstly, it quantitatively captures economic activity from the supply-side perspective of the global supply chain, rendering it a highly useful and versatile indicator. Conventional similar indicators only capture the situation of individual countries/regions' supply chains, whereas GSCPI aggregates data from seven countries/regions, which are significant international trade hubs in the global supply chain, into a single time series, thus depicting the state of the global supply chain on a worldwide scale. Additionally, the PMI data used in the construction of GSCPI are influenced by both demand and supply sides, and by removing demand-side elements such as new orders and purchasing volumes through statistical processing, supply-side factors such as supply chain delays and stagnation are extracted. Figure 2 illustrates the GSCPI from January 1998 to November 2023. When the data is greater than 0, it indicates that the global supply chain is under more strain than usual. The periods of significant strain on the supply chain, such as during the Tohoku Earthquake and Tsunami in March 2011, the Thailand Floods from from July 2011 to January 2012, and the onset of the COVID-19 pandemic since 2020, are discernible from Figure 2, where GSCPI shows a significant increase above 0, indicating a considerable impact on the supply chain and heightened strain compared to peacetime conditions.

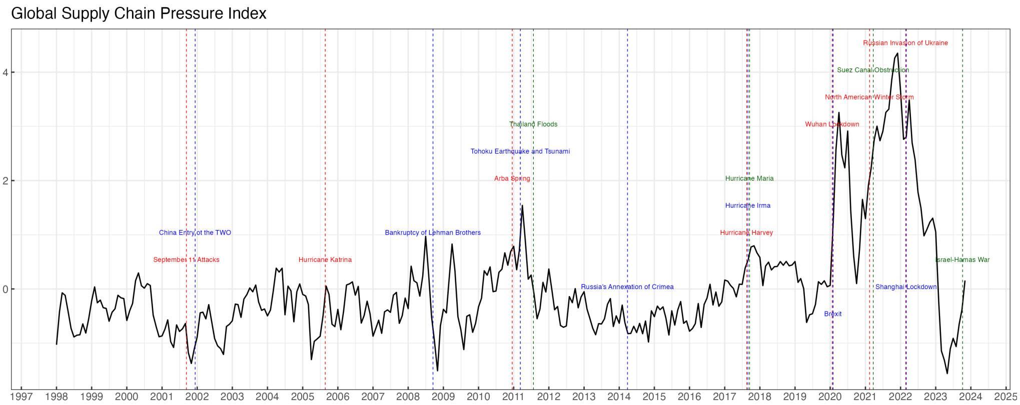


Figure 2: Global Supply Chain Pressure Index (January 1998 - November 2023)

Since its publication, the GSCPI has been utilized in numerous empirical studies as a time-series indicator to capture the strain on the global supply chain on a monthly basis. Benigno et al. (2022) applied the local projection method proposed by Jordà (2005) to investigate the relationship between the supply chain situation and recent inflation trends. They found that fluctuations in GSCPI, particularly in relation to producer price indices in the United States and Europe, significantly contribute to producer price inflation. Finck and Tillmann (2022) concluded that supply chain shocks lead to a decline in production activities and an increase in consumer prices in Europe, with approximately 30% of inflation volatility explained by supply chain shocks. Furthermore, their study, based on regional data, revealed that supply chain

[3] A price index representing air freight costs from the United States to Europe and Asia, as well as from Europe and Asia to the United States, as published by the Bureau of Labor Statistics (BLS) in the United States.

[4] Delivery time, backlogs and purchase stocks.

[5] Europe, Mainland China, Japan, South Korea, Taiwan, the United Kingdom, and the United States.

shocks originating from China primarily affect production activities, while those from regions other than China affect consumer prices. Bolhuis et al. (2022) examined the impact of supply chain shocks on consumer prices in 29 countries in sub-Saharan Africa. Moreover, their study suggested policy implications, indicating that monitoring the situation of the supply chain represented by GSCPI by central banks and adjusting the stance of monetary policy promptly until the effects of supply chain shocks fully propagate could effectively stabilize prices and production. Kabaca and Tuzcuoglu (2023) focused on recent high inflation in the United States and identified supply chain shocks using GSCPI, oil prices, policy rates, labor force participation rates, and other macroeconomic data in a structural VAR model. They concluded that supply chain shocks and oil price shocks are major contributors to high inflation. While GSCPI is created based on the statistical processing of existing data to generate new indicators, Kliesen and Werner (2022) took a different approach by analyzing the text of the Beige Book[6] published by the Federal Reserve Bank of the United States using natural language processing techniques to create the Beige Book Supply Chain Disruption Index (BBSCDI), which counts keywords[7] related to supply chain disruptions. In contrast, Soto (2023) utilized unsupervised machine learning to identify additional keywords beyond the specified ones, such as "shortages," "delays," and "disruptions," from the context of the Beige Book to create the Supply Chain Bottleneck Sentiment Index (SCBSI) to more accurately capture the strain on the supply chain. Moreover, Soto (2023) conducted empirical analysis using GSCPI, BBSCDI, and SCBSI to identify supply chain shocks and examine their impact on the inflation rate in the United States using a time-varying coefficient VAR model proposed by Primiceri (2005). They concluded that the effects of supply chain shocks on prices decay slowly, leading to sustained inflationary pressures.

Although these three indices exhibit high correlation and similar trends in data fluctuations, BBSCDI and SCBSI capture the supply chain situation based on keywords identified from the Beige Book using natural language processing techniques, representing the economic conditions within the United States. In contrast, GSCPI captures the situation of the global supply chain by aggregating a broader range of data statistically, making it more suitable for empirical analysis outside the United States. Taking into consideration the generality of the empirical methodology and data of the preceding studies, this paper employs GSCPI to investigate the impact of the global supply chain situation on the Japanese economy. As for the empirical methodology, we utilize the GSCPI to examine the dynamic effects of supply chains on production and prices through local projection. Furthermore, we decompose the fluctuations in prices and production into contributions from various exogenous shocks affecting the economy, using techniques such as historical decomposition and variance decomposition in a structural VAR model, to calculate how much each shock can explain the fluctuations in prices and production in the long run. Simultaneously, we investigate the influence of energy prices and food prices as representative examples of raw commodity prices affecting prices and production using the same method.

Here, we first present some conclusions as a summary. We divide the data into full sample and subsample, with the full sample covering the period after 2020 during the pandemic, while the subsample ends in December 2019. In the analysis using the subsample before the pandemic, we find that the impact of the supply chain on prices and output was very limited,

[6]The Beige Book is a report that summarizes the economic conditions in each region as published by the Federal Reserve Banks of the Federal Reserve System. For more details, please refer to https://www.federalreserve.gov/monetarypolicy/publications/beige-book-default.htm.

[7]The frequency of keywords such as "supply chain," "bottleneck," "backlog," "port," "unfilled order," "delivery time," "supply delay," "truck," "boat," and "transportation" is counted, and the higher the frequency of these keywords, the higher the perceived tightness of the supply chain.

at least in terms of statistical significance. However, in the analysis incorporating the full sample including the pandemic period, we find that disruptions in the supply chain immediately lead to changes in prices and output, manifesting as a sustained increase in prices and a temporary decline in output. From the historical decomposition of the structural VAR model, it can be observed that the demand rebound after the stabilization of the pandemic and the sustained tension in the supply chain are the main reasons for the rise in the price index from early 2021 to the end of 2022. This conclusion is consistent with findings from similar studies on developed economies in Europe and the United States. In this paper, we did not extensively discuss the impact of the Bank of Japan's monetary policy on the Japanese economy after 2020. Exploring how to address the impact of supply chains on the macroeconomy from the perspective of monetary policy is a very novel question. When discussing the impact of supply chain disruptions on the macroeconomy, the majority of existing studies have relied on time-series econometric methods, failing to provide normative economic discussions based on theoretical modeling frameworks. There is a scarcity of literature offering normative modeling of this issue, primarily because, before the pandemic, the impact of supply chains on the macroeconomy was relatively limited, with disruptions caused by natural disasters affecting specific industries rather than the entire macroeconomic activity. However, post-pandemic, supply chain disruptions have affected various industry sectors. This assertion is also supported by our analysis of impulse responses estimated from a pre-pandemic subsample. Zanetti et al. (2024) have presented a good market model framework based on search and matching theory to address this issue. Through a comparative static analysis, they examined the impact of supply chain shocks on production and prices and discussed monetary policy implications based on the model. However, their model remains relatively simple and cannot analyze the complex dynamic relationships between variables. The primary role of this theoretical framework is to qualitatively analyze the effects of various shocks on the macroeconomy, thereby providing a theoretical basis for shock identification in VAR models. We will discuss some future research directions regarding the supply chain and macroeconomy in the Section 4.

The structure of this paper is explained as follows. In Section 2, we introduce the details of the data. In Section 3, we explain the methodology of empirical analysis and interpret the impulse responses calculated from local projection, as well as the variance decomposition and historical decomposition calculated from the structural VAR model. In Section 4, we summarize the above contents and provide prospects for future research.

2 Data

This paper utilizes monthly time series data from January 1998 to November 2023. The variable names and data sources can be confirmed from Table 1.

Variable	Data	Data Source
GSCPI	Global Supply Chain Pressure Index	Federal Reserve Bank of New York
ENERGY	Global Price of Energy Index (YoY%)	International Monetary Fund
FOOD	Global Price of Food Index (YoY%)	International Monetary Fund
CPI	Consumer Price Index (YoY%)	Statistics Bureau of the Ministry of Internal Affairs and Communications
PPI	Producer Price Index (YoY%)	Bank of Japan
GDP	Monthly Real GDP (YoY%)	NLI Research Institute
CON	Monthly Real Private Consumption (YoY%)	NLI Research Institute
SSR	Short-Term Shadow Rate	Krippner (2020)

Table 1: Variable and Data Source

The GSCPI, which indicates the tightness of global supply chains, is a unitless index without clear seasonality. Therefore, the original series is used directly. Energy prices and food prices utilize the IMF Primary Commodity Prices, which are published by the International Monetary Fund. Since many previous studies focus on the US economy, they use crude oil prices denominated in dollars as data for energy prices. However, considering empirical analysis on the Japanese economy, this paper simply uses price indices representing fluctuations in energy prices and food prices globally to avoid converting oil prices by exchange rates. Regarding prices, both the Consumer Price Index (CPI) and the Producer Price Index (PPI) are used to observe the impacts of supply chain shocks and commodity price shocks on each price index.

For production, the monthly real GDP (GDP) and real private consumption (CON), estimated by NLI Research Institute, are utilized. Lastly, concerning the stance of monetary policy, which significantly affects production and prices, Japan has maintained a zero interest rate for many years. Therefore, instead of the call rate, this paper uses the short-term shadow rate (SSR) estimated by Krippner (2020). The short-term shadow rate takes the same value as the normal policy rate when it is zero or higher. However, during periods of unconventional monetary policy, while the normal policy rate remains at zero, the shadow rate takes negative values, indicating a loosening of monetary policy when falling and a tightening when rising, thus consistently representing the stance of monetary policy[8]. Many previous studies have effectively used the shadow rate as an interest rate indicator capturing the stance of monetary policy similar to traditional policy rates. Wang (2019a, 2019b) provides an example of applying the shadow rate to the Japanese economy, demonstrating that it can consistently represent the stance of unconventional monetary policy since the Bank of Japan's zero interest rate era.

[8] The shadow rate, even if it falls into negative territory, signifies monetary easing when it declines and monetary tightening when it rises.

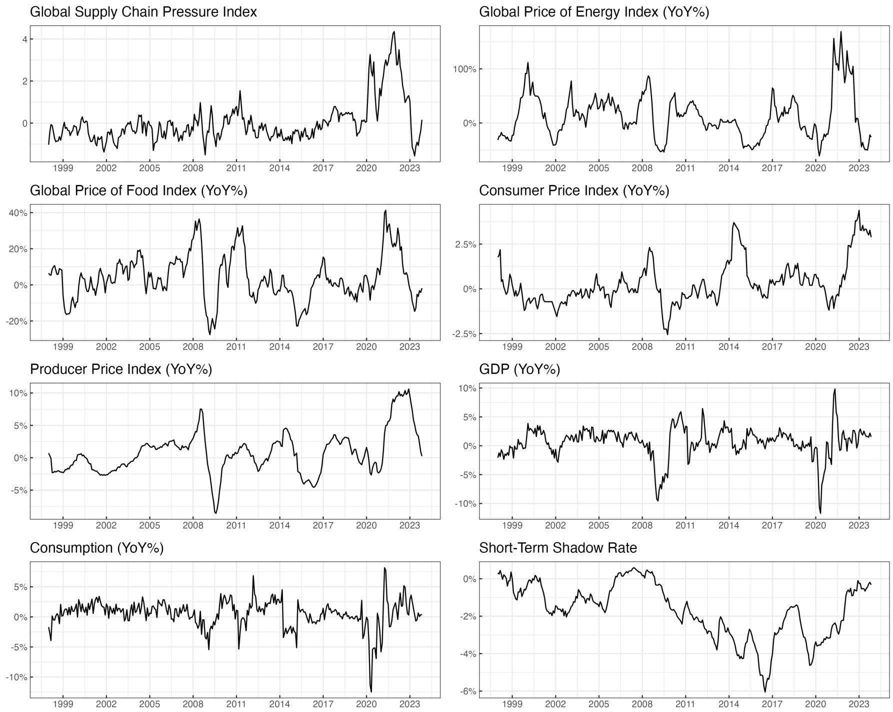


Figure 3: Dataset

Regarding data processing, raw data with obvious seasonality is converted into percentage changes from the corresponding period of the previous year to remove the influence of seasonal fluctuations. Since 2020, energy prices and food prices have risen significantly compared to previous years, while consumer prices and producer prices have also increased substantially. Concerning production, Japan, like other major advanced countries, experienced a temporary significant decline after the onset of the COVID-19 pandemic, followed by a V-shaped recovery, as evident from Figure 3.

3 Econometric Models and Empirical Results

In this paper, we refer to previous studies to estimate the dynamic relationships between variables using local projection. Furthermore, we estimate a structural VAR model to investigate the impact of exogenous shocks on Japan's macroeconomy through variance decomposition and historical decomposition.

3.1 Local Projection

We follow the methodology proposed by Jordà (2005) to estimate the dynamic relationships between variables using local projection, which are widely applied in time series analysis. Recent econometric theoretical studies, such as Montiel and Plagborg-Moller (2022) and Plagborg-Moller and Wolf (2021), have demonstrated that local projection estimation provides impulse responses comparable to those obtained from conventional VAR models, while also showing robustness of estimates and high generality with respect to the data. Following the approach of Benigno et al. (2022), we estimate the following formulation

$$y_{t+h} = \alpha_h + \boldsymbol{\beta}_h' \boldsymbol{x}_t + \boldsymbol{\gamma}_h' \boldsymbol{z}_t + \varepsilon_{t+h}$$

where y_{t+h} represents either the price (CPI or PPI) or the output (GDP or CON) at time $t+h$, $\boldsymbol{x}_t$ is a vector of exogenous variables (GSCPI, ENERGY, and FOOD), α_h represents the constant term, and the estimated coefficient series $\{\boldsymbol{\beta}_h,\ h = 1, 2, \cdots, H\}$ represents the impact of the exogenous variables $\boldsymbol{x}_t$ on y_{t+h}. $\boldsymbol{z}_t$ includes lagged variables of y_t as control variables. While it could be argued that since the source data for GSCPI is originally from the Japanese economy, and energy prices (ENERGY) and food prices (FOOD) are influenced to some extent by the supply-demand situation in the Japanese economy, they could be treated as endogenous variables. However, here we consider their impact to be limited, and treat these variables as exogenously given with respect to the Japanese economy. The estimated coefficient series $\{\boldsymbol{\beta}_h,\ h = 1, 2, \cdots, H\}$ are a type of impulse response known as dynamic multipliers. Taking the length of the coefficient series to be $H = 24$, we estimate the impact of the variation in exogenous variables $\boldsymbol{x}_t$ at the current time point on y_t up to 2 years ahead. As for the choice of lag order p for the control variables $\boldsymbol{z}_t$, we set $p = 3$ to control for the influence of the past 3 periods (3 months) of realizations of y_t on the current y_t. Regarding the selection of the lag order for the control variables $\boldsymbol{z}_t$, we compared the estimation results using lag numbers such as $p = 6$ and $p = 8$ to check for robustness, and found that there were no significant changes in the dynamic multipliers' graphs. Therefore, in this paper, we report the estimation results of the coefficient series $\{\boldsymbol{\beta}_h,\ h = 1, 2, \cdots, H\}$ obtained when $p = 3$ as the benchmark. For the estimation period, we conduct separate estimations for the full sample period including the COVID-19 and Ukraine invasion (January 1998 to November 2023) and the pre-COVID-19 subsample period (January 1998 to December 2019) to examine the differences in the impact of supply chain tightness and the fluctuations in energy and food prices on Japan's prices and production before and after the onset of COVID-19. Figures 4 to 15 present the impulse responses based on local projection. The solid lines with markers in the figures represent the mean estimates of the coefficient sequence, while the ribbons represent the 95% confidence intervals.

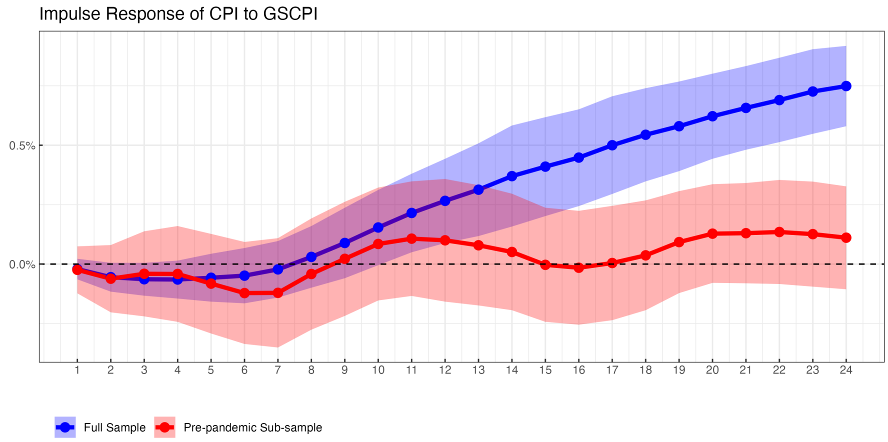


Figure 4: Impulse Response of CPI to GSCPI

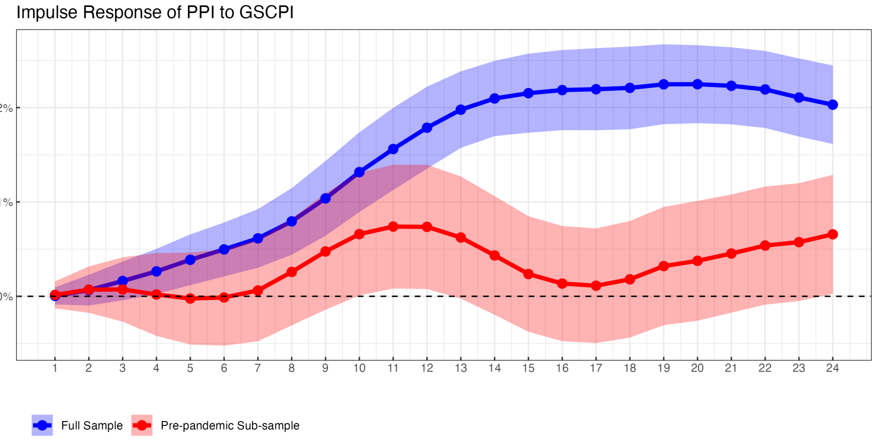


Figure 5: Impulse Response of PPI to GSCPI

From Figure 4, it can be observed that the impulse response estimated from pre-pandemic subsample is not statistically significant, indicating that supply chain fluctuations do not significantly impact consumer prices. However, this phenomenon changes after the pandemic. The impulse response estimated from the full sample is not significant in the first 10 periods, but from the 10th period onwards, shocks from the supply chain significantly lead to sustained increases in consumer prices, and their impact does not diminish in the short term. This phenomenon is actually in line with economic intuition. Prices have a certain rigidity and cannot quickly adjust to external shocks, so consumer prices react with a certain lag to fluctuations in the supply chain. In Figure 5, we can observe a similar phenomenon. In the pre-pandemic subsample, the impulse response estimated indicates that supply chain fluctuations almost do not affect producer prices. The increase in producer prices caused by supply chain fluctuations is statistically significant only between the 10th and 13th periods. However, in the impulse response obtained from the full sample, producer prices respond rapidly to shocks from the supply chain. From the 4th period onwards, supply chain fluctuations lead to sustained increases in producer prices, and their impact does not diminish in the short term either.

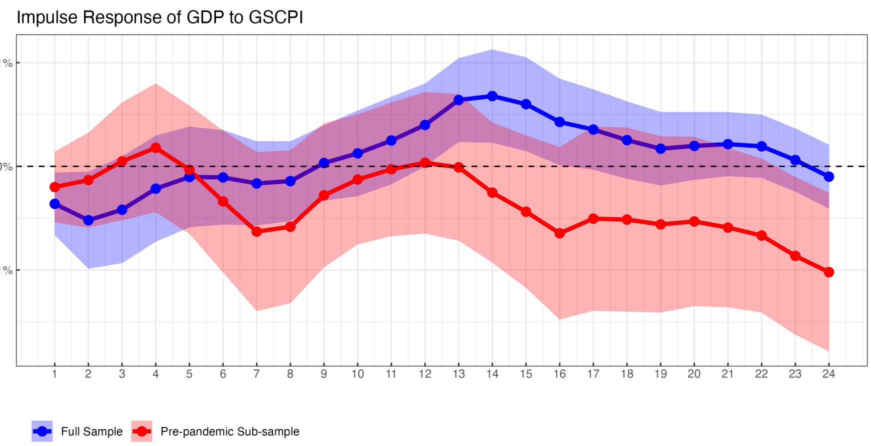


Figure 6: Impulse Response of GDP to GSCPI

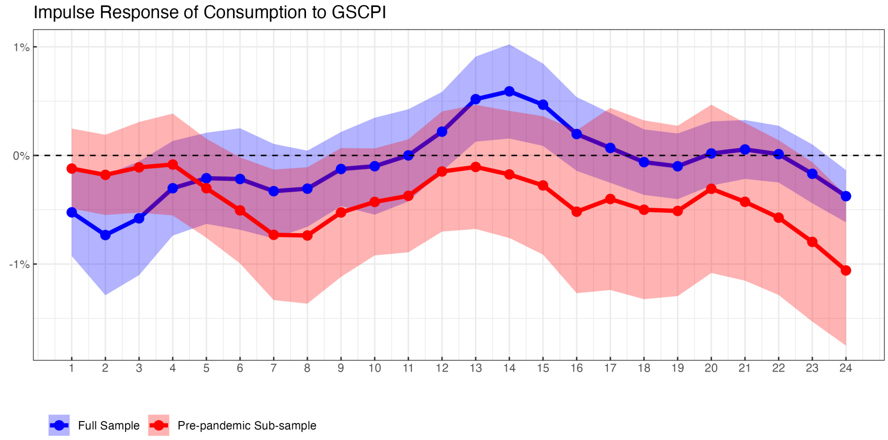


Figure 7: Impulse Response of CON to GSCPI

Let's take a look at the impact of supply chain fluctuations on GDP and consumption based on Figures 6 and 7. Overall, the impulse response estimated from the pre-pandemic subsample indicates that although supply chain fluctuations do not significantly affect GDP and consumption in terms of statistical significance, there is a negative trend in their impact. Looking at the impulse response obtained from the full sample estimation, within the 1 to 2 period range, supply chain fluctuations lead to a decline in real GDP, while between periods 12 to 16, GDP responds positively to supply chain fluctuations. The response of consumption to supply chain fluctuations is similar to that of GDP. Within periods 1 to 3, consumption experiences a brief decline due to supply chain influences, but between periods 12 to 16, consumption shows a brief increase. These empirical findings are consistent with the macroeconomic activities observed after 2020. Under the influence of the pandemic, economic activities experienced a sharp short-term stagnation followed by a brief period of strong recovery.

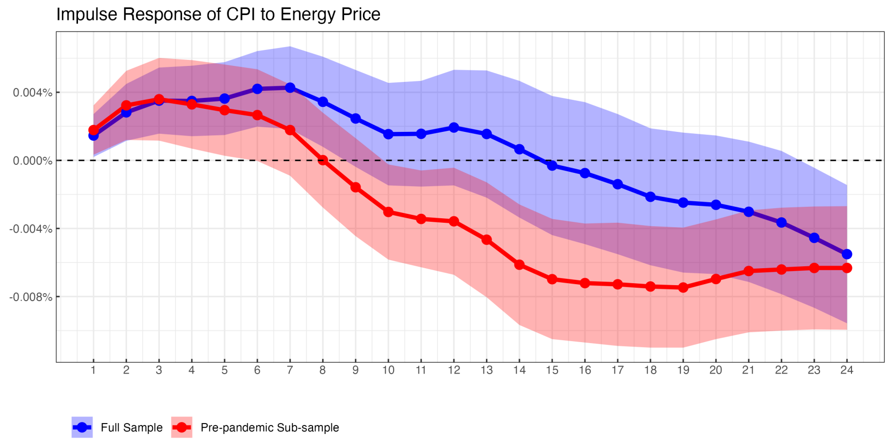


Figure 8: Impulse Response of CPI to ENERGY

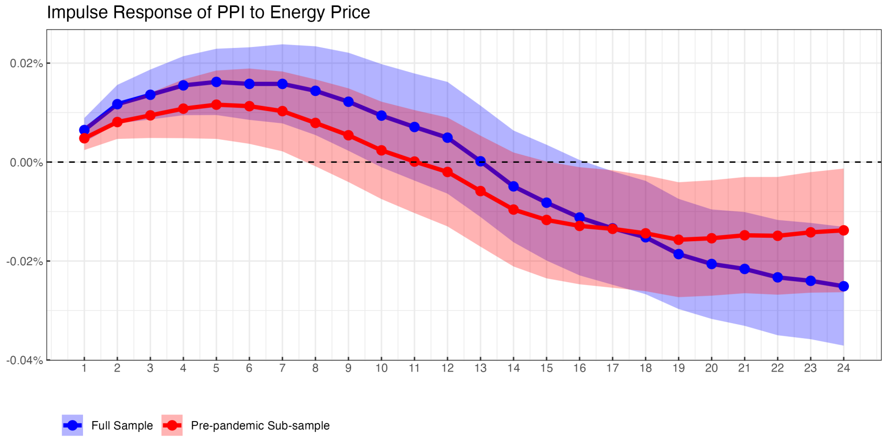


Figure 9: Impulse Response of PPI to ENERGY

Figure 8 and Figure 9 respectively demonstrate the impact of energy prices on consumer prices and producer prices. The influence of energy prices on producer prices is significantly greater in magnitude (by a factor of 10 in percentage terms) than on consumer prices. Following a shock from energy prices, both consumer and producer prices will rise rapidly in the short term, but in the long term, this effect will gradually diminish. Impulse response estimated from pre-pandemic subsample indicates that both types of prices will decline in the long term after being hit by energy price shocks.

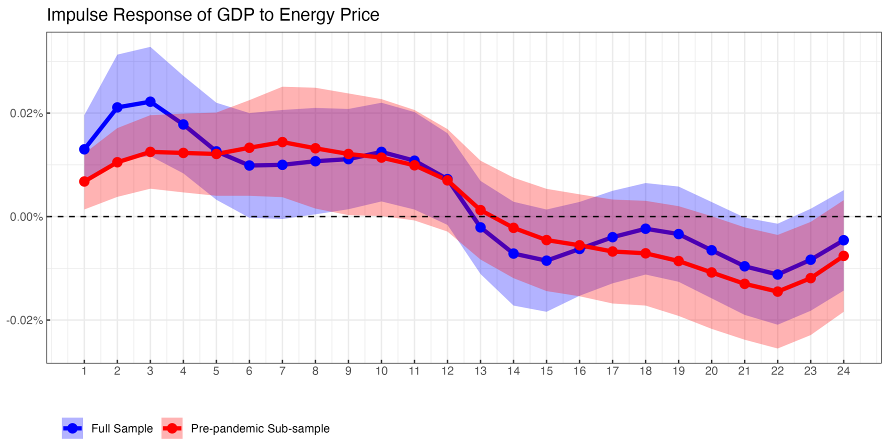


Figure 10: Impulse Response of GDP to ENERGY

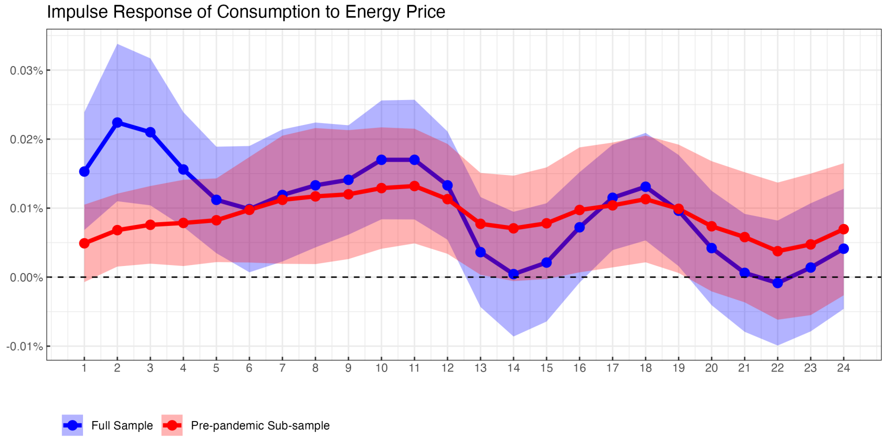


Figure 11: Impulse Response of CON to ENERGY

Figure 10 and Figure 11 respectively illustrate the impact of energy prices on GDP and consumption. We observe that under the influence of rising energy prices, both GDP and consumption increase. In fact, this phenomenon is not counterintuitive from an economic perspective because in System of National Account (SNA), GDP consumption data are based on the demand side, and the increase in energy prices can lead to an increase in consumption expenditure to some extent.

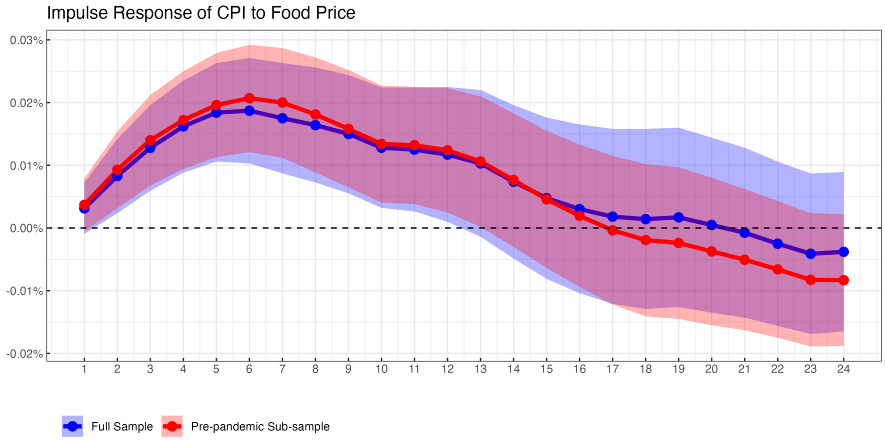


Figure 12: Impulse Response of CPI to FOOD

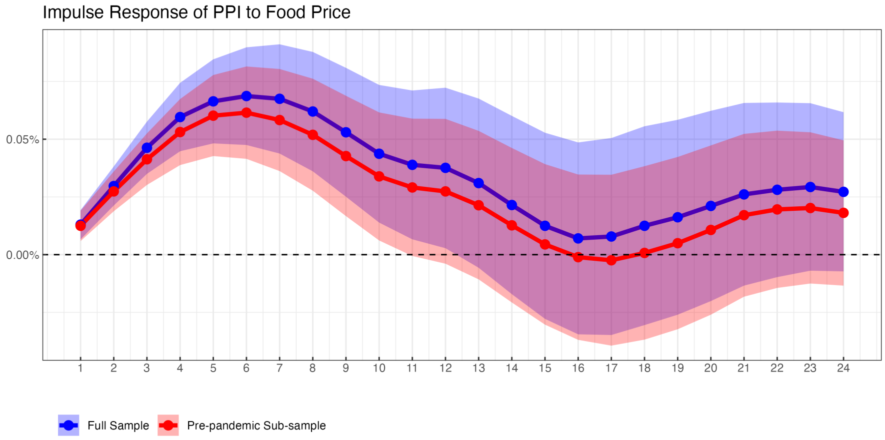


Figure 13: Impulse Response of PPI to FOOD

Finally, let's take a look at the impact of food prices on consumer and producer prices. As shown in Figure 12 and Figure 13, the impulse responses obtained for the full sample and pre-pandemic subsample are similar. The rise in food prices leads to a sustained increase in prices, with its effect lasting for about one year.

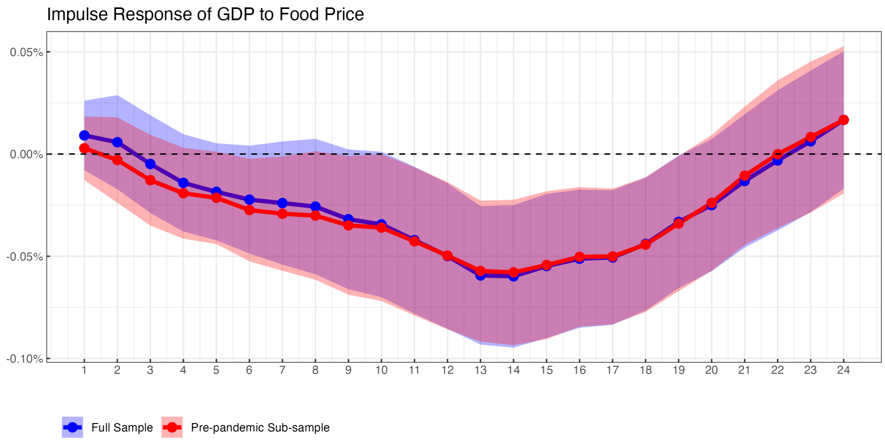


Figure 14: Impulse Response of GDP to FOOD

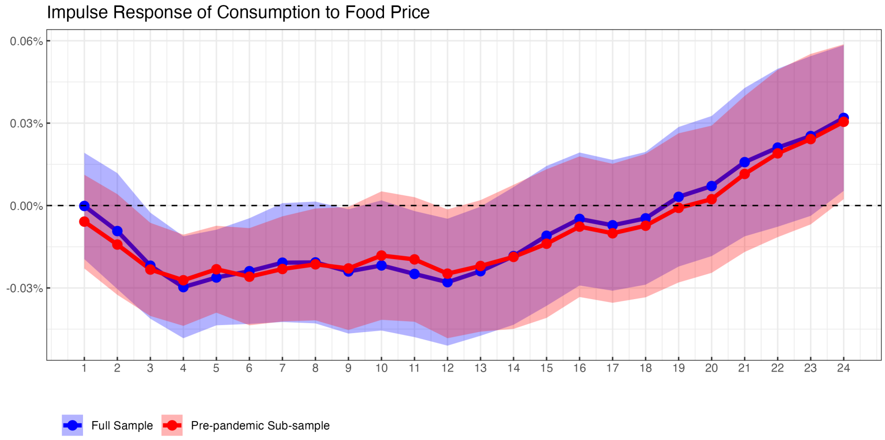


Figure 15: Impulse Response of CON to FOOD

From Figure 14 and Figure 15, we can observe that the rise in food prices has statistically insignificant effects on GDP and consumption for the most part. It only leads to short-term declines in certain time periods. The suppressive effect of rising food prices on consumption is statistically significant only within a six-month period. This phenomenon holds true for both the full sample and pre-pandemic subsample.

3.2 Structural VAR

The dynamic multipliers estimated in the aforementioned local projection consider unilateral effects between variables. However, in reality, prices and production interact with each other, being simultaneously influenced by supply chain strain, fluctuations in commodity prices, and monetary policy. Based on this perspective, it is considered appropriate to estimate a Vector Autoregression (VAR) model that consolidates multiple variables into a single dynamic system. Following the approach of Kabaca and Tuzcuoglu (2023), this paper estimates a reduced-form VAR model with six variables and identifies structural shocks based on sign restrictions.

$$\boldsymbol{Y}_t = \boldsymbol{A}_0 + \boldsymbol{A}_1 \boldsymbol{Y}_{t-1} + \cdots + \boldsymbol{A}_p \boldsymbol{Y}_{t-p} + \boldsymbol{u}_t$$

$\boldsymbol{Y}_t = [\mathrm{GSCPI}_t,\ \mathrm{ENERGY}_t,\ \mathrm{FOOD}_t,\ \mathrm{CPI}_t(\mathrm{PPI}_t),\ \mathrm{GDP}_t(\mathrm{CON}_t),\ \mathrm{SSR}_t]'$ represents the vector of six endogenous variables. $\boldsymbol{A}_0,\ \boldsymbol{A}_1, \cdots,\ \boldsymbol{A}_p$ denote the coefficient matrices of size 6×6. $\boldsymbol{u}_t$ represents the error term of the reduced-form VAR model, and follows a normal distribution $\boldsymbol{u}_t \sim \mathcal{N}(0, \Sigma)$. Here, Σ denotes the variance-covariance matrix of the error term $\boldsymbol{u}_t$. Typically, the error term $\boldsymbol{u}_t$ represents the residuals of the estimated equations without economic interpretation. Therefore, it is necessary to transform the reduced-form VAR model into a structural VAR model to identify structural shocks with economic interpretations. Denoting the vector of structural shocks in the structural VAR model as $\boldsymbol{\varepsilon}_t$, the following relationship holds between $\boldsymbol{\varepsilon}_t$ and $\boldsymbol{u}_t$.

$$\boldsymbol{u}_t = \boldsymbol{D}\boldsymbol{\varepsilon}_t$$

$$\Sigma = \mathbb{E}(\boldsymbol{u}_t \boldsymbol{u}_t') = \mathbb{E}(\boldsymbol{D}\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t' \boldsymbol{D}') = \boldsymbol{D}\mathbb{E}(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t')\boldsymbol{D}' = \boldsymbol{D}\boldsymbol{\Gamma}\boldsymbol{D}'$$

$\boldsymbol{\Gamma}$ represents the variance-covariance matrix of the structural shocks $\boldsymbol{\varepsilon}_t$. Typically, since each structural shock is uncorrelated with each other and orthogonal, $\boldsymbol{\Gamma}$ is a diagonal matrix. $\boldsymbol{D}$, known as the contemporaneous impact matrix, is required to be estimated to recover the structural shocks $\boldsymbol{\varepsilon}_t$ from the error terms $\boldsymbol{u}_t$. This process is called shock identification, and there are several methods for identifying structural shocks, such as short-run/long-run restrictions, sign restrictions, instrumental variables, etc. Among them, the method of sign restrictions, which imposes restrictions on the direction of responses of endogenous variables in the impulse responses, is commonly used based on empirical evidence and economic theory. For identifying structural shocks using sign restrictions, algorithms such as Uhlig (2005), Rubio-Ramirez et al. (2010), and Arias et al. (2018) have been proposed. In this paper, we adopt the algorithm proposed by Arias et al. (2018) and implemented in the BEAR toolbox[9]. Table 2 shows the specific settings of sign restrictions for identifying structural shocks from endogenous variables. While referring to Kabaca and Tuzcuoglu (2023), we also incorporate the results of the aforementioned local projection. The interpretation of the identified structural shocks and the associated sign restrictions are as follows. The supply chain shock not only induces strain within the supply chain itself but also leads to production delays, logistical disruptions, and supply shortages, resulting in increases in energy and food prices as well as consumer and producer prices. Regarding the impact of the supply chain shock on production, since there is limited interpretation based on theoretical models, we follow the assumption that the supply chain shock reduces production, consistent with the results in Figure 6 and Figure 7. The increase in energy prices raises transportation costs, contributing to strain within the supply chain. As for the food price shock, since its effects on the supply chain and energy prices are uncertain, we do not specify the signs. Generally, according to Smets and Wouters (2007), consumer/producer price markup shocks lead to a decrease in production and an increase in prices. Moreover, as a general principle in macroeconomics, aggregate demand shocks move production and prices in the same direction. Finally, regarding monetary policy shocks, when representing monetary easing, an interest rate cut leads to increases in prices and production. Since monetary policy is not adjusted based on individual prices of goods, and global energy and food prices are not entirely influenced by Japanese monetary policy, we do not specify sign restrictions for these shocks.

Variable/Structural Shock	Supply Chain	Energy Price	Food Price	Consumer/Producer Price Markup	Aggregate Demand	Monetary Policy
GSCPI	+	+				
ENERGY	+	+				
FOOD	+	+	+			
CPI/PPI	+	+	+	+	+	+
GDP/CON	-	-	-	-	+	+
SSR					+	-

Table 2: Identification of Structural Shocks through Sign Restrictions

During the model estimation, the Minnesota distribution is chosen as the prior distribution. As a robustness check, different prior distributions (Normal-Diffuse, independent Normal-Wishart) yield similar results in subsequent analyses such as variance decomposition and historical decomposition. The choice of lag order p for the endogenous variables is based on information criteria for the reduced form model, where $p = 3$ is selected. Although estimations were also conducted for formulations with $p = 6$, $p = 8$, and $p = 12$, the results did not vary significantly, thus this paper reports the estimation results for $p = 3$ as the benchmark.

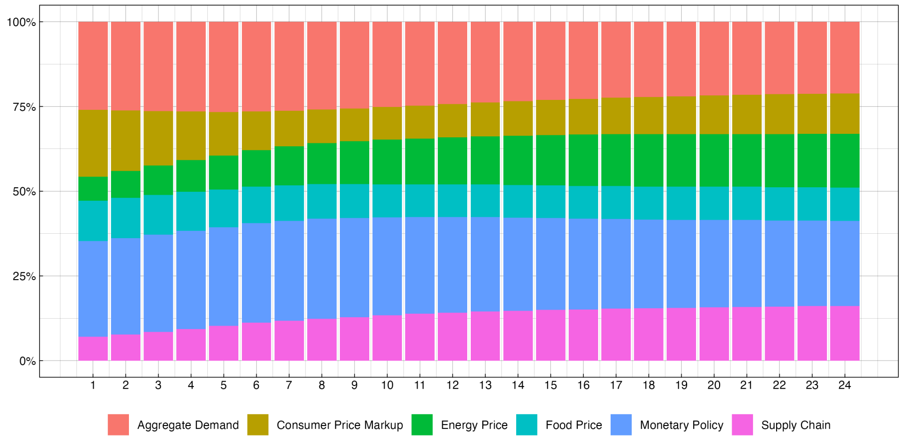
Among the six variables, namely prices and output, we estimated four models by combining different data: two price indices (CPI and PPI) and two output data (GDP and CON). The

[9]The BEAR toolbox (Bayesian Estimation, Analysis and Regression toolbox) is a Bayesian estimation tool for VAR models developed by the European Central Bank (ECB). For more details, please refer to https://github.com/european-central-bank/BEAR-toolbox.

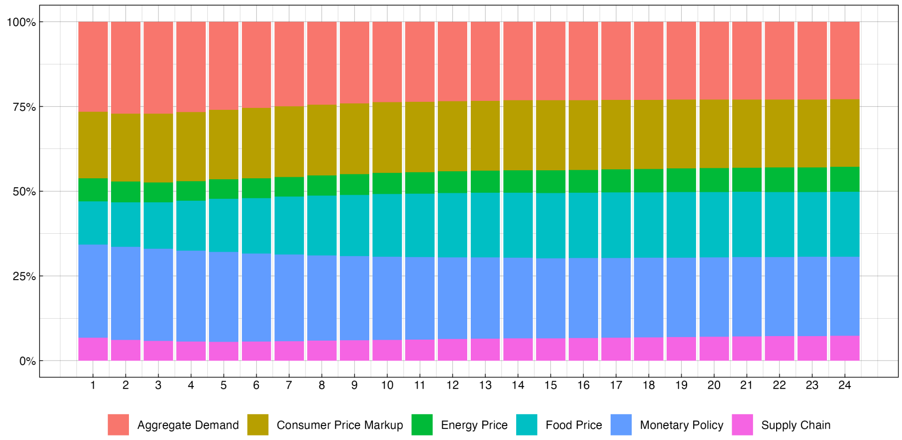
models are referred to as follows: the CPI-GDP-version model when using CPI and GDP, the CPI-CON-version model when using CPI and CON, the PPI-GDP-version model when using PPI and GDP, and the PPI-CON-version model when using PPI and CON. The other four variables (GSCPI, ENERGY, FOOD and SSR) are common across all four models. Using the estimated structural VAR model, this paper conducts variance decomposition and historical decomposition. Since impulse responses from the VAR model are determined by sign restrictions and analyses on impulse responses have been already conducted based on the previously mentioned local projection, this paper does not extensively explain the impulse responses from the VAR model. For the impulse responses calculated from the VAR model with sign restrictions, please refer to Figure 25, Figure 26, Figure 27 and Figure 28.

3.3 Variance Decomposition

Here are some conclusions we derived from observing the variance decomposition plots. By comparing Figure 16, Figure 17, Figure 18 and Figure 19, we find that, firstly, the results of variance decomposition from the four models are generally similar. Supply chain shock have a greater explanatory power for the variance of price variables (CPI and PPI) than for output variables (GDP and CON). The impact of supply chain shock on price variables (CPI and PPI) is increasing, while its impact on output variables (GDP and CON) remains relatively constant over time. The impact of energy price shock on price variables (CPI and PPI) gradually increases, while its impact on output variables (GDP and CON) remains relatively stable over time, showing little variation. The impact of aggregate demand shock on CPI remains relatively stable, while its impact on PPI gradually weakens. Aggregate demand shock also exhibit a relatively stable impact on output variables (GDP and CON), showing little variation over time. The impact of monetary policy shock on output variables (GDP and CON) and CPI remains relatively stable over time, but its effect on PPI shows a declining trend. Price markup shocks have a relatively stable impact on output variables (GDP and CON), while their impact on price variables (CPI and PPI) shows a trend of weakening and then increasing.

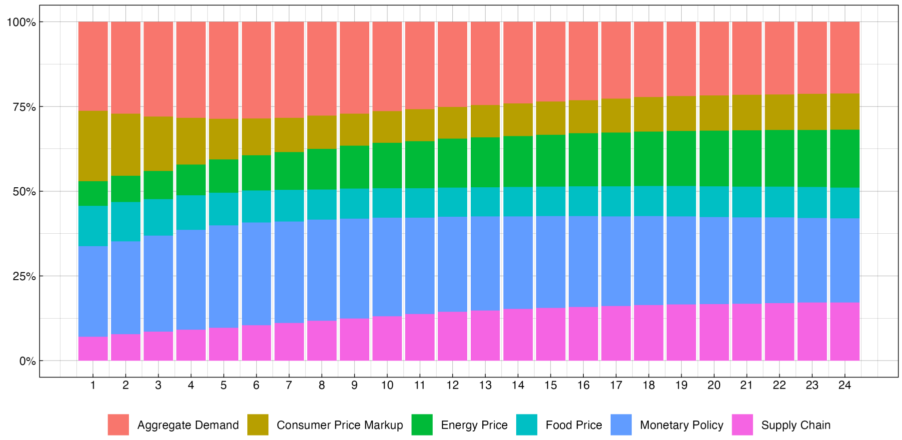


(a) Variance Decomposition of CPI

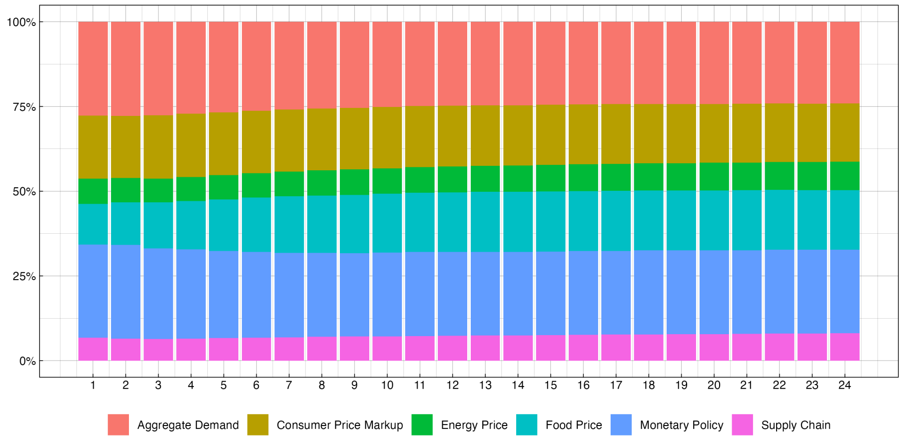


(b) Variance Decomposition of GDP

Figure 16: Variance Decomposition CPI-GDP-version model

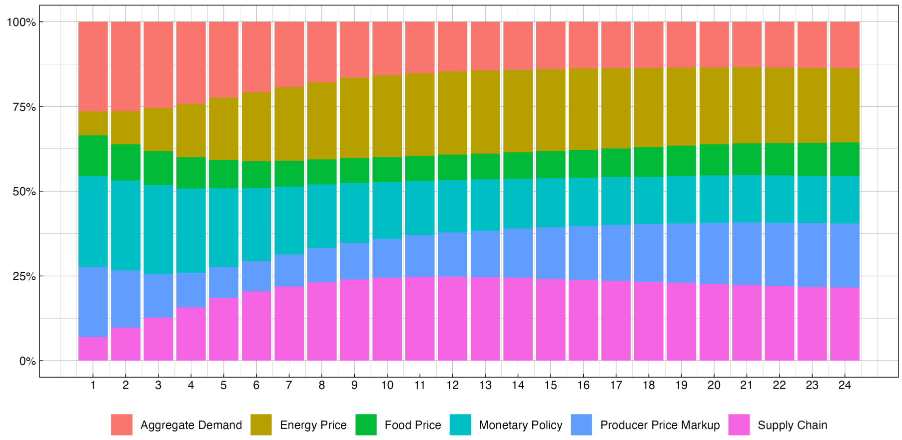


(a) Variance Decomposition of CPI

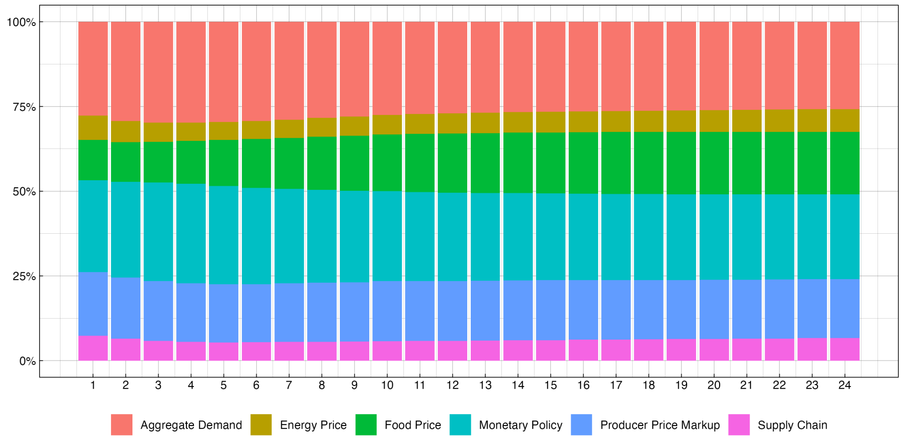


(b) Variance Decomposition of Consumption

Figure 17: Variance Decomposition CPI-CON-version model

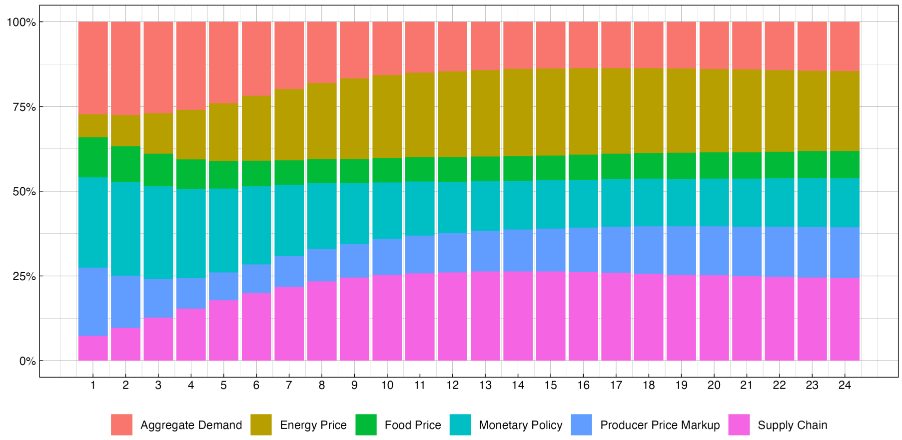


(a) Variance Decomposition of PPI

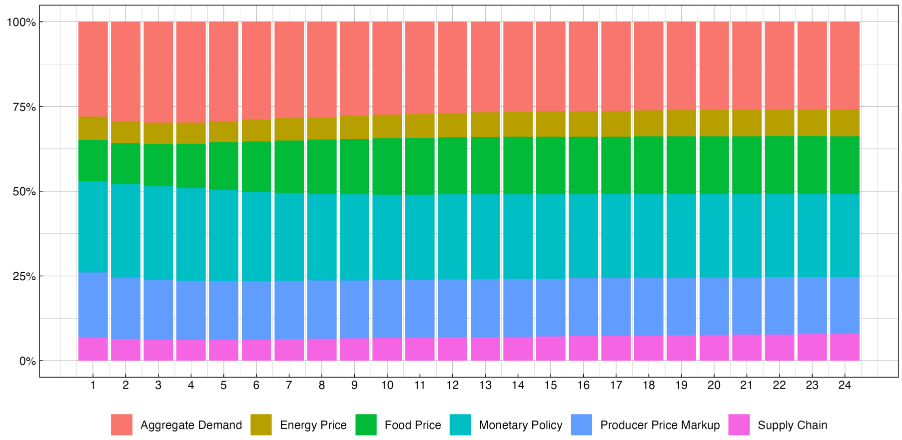


(b) Variance Decomposition of GDP

Figure 18: Variance Decomposition PPI-GDP-version model



(a) Variance Decomposition of PPI



(b) Variance Decomposition of Consumption

Figure 19: Variance Decomposition PPI-CON-version model

We averaged the variance decomposition data over 24 periods and summarized the results in Figure 20. We processed the calculation results similar to a heat map, enabling a better visualization of the impacts of different shocks on price and output variables. Ignoring minor differences in the results of the four models and integrating the findings from Figure 20, it can be concluded that supply chain shocks, energy price shocks, and food price shocks can explain approximately 36% of the variance in CPI and about 50% of the variance in PPI. Moreover, the explanatory power of these three shocks for the variance in GDP and consumption is around 30%. Adding price markup shocks, these four supply-side shocks account for roughly half of the variance in prices and output. Meanwhile, aggregate demand shock and monetary policy shock, representing demand-side shocks, precisely explain the remaining half of the variance in prices and output.

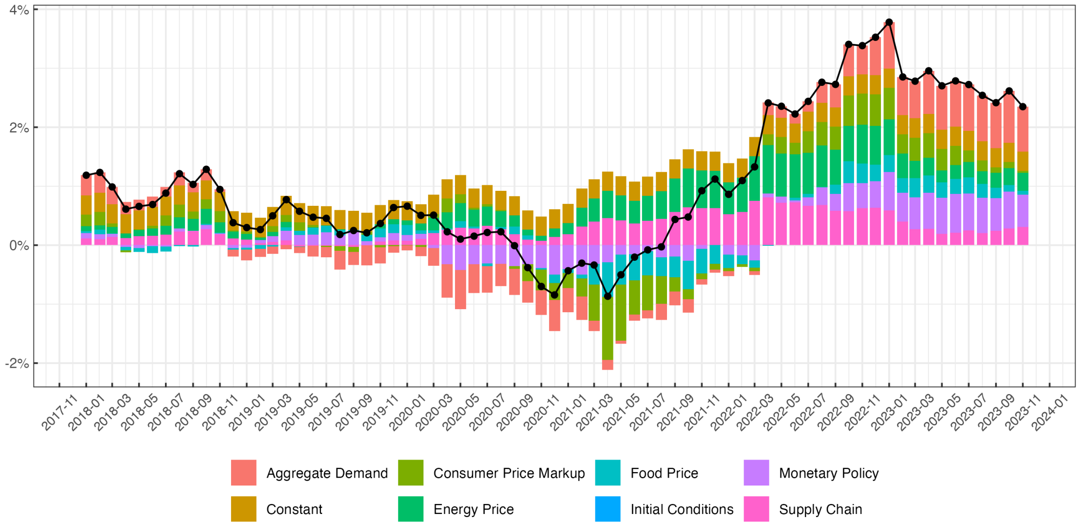
		Supply Chain Shock	Energy Price Shock	Food Price Shock	Consumer Price Markup Shock	Aggregate Demand Shock	Monetary Policy Shock
CPI-GDP-version model	CPI	13.24%	13.09%	10.22%	11.84%	24.04%	27.58%
	GDP	6.46%	6.51%	17.76%	20.43%	24.16%	24.67%
		Supply Chain Shock	Energy Price Shock	Food Price Shock	Producer Price Markup Shock	Aggregate Demand Shock	Monetary Policy Shock
PPI-GDP-version model	PPI	21.03%	21.00%	8.66%	14.54%	17.09%	17.69%
	GDP	6.08%	6.04%	16.39%	17.56%	27.38%	26.54%
		Supply Chain Shock	Energy Price Shock	Food Price Shock	Consumer Price Markup Shock	Aggregate Demand Shock	Monetary Policy Shock
CPI-CON-version model	CPI	13.53%	13.43%	9.32%	11.30%	24.87%	27.55%
	CON	7.32%	7.69%	16.62%	17.92%	25.28%	25.17%
		Supply Chain Shock	Energy Price Shock	Food Price Shock	Producer Price Markup Shock	Aggregate Demand Shock	Monetary Policy Shock
PPI-CON-version model	PPI	22.30%	21.61%	7.94%	12.53%	17.59%	18.03%
	CON	6.99%	7.18%	15.84%	17.18%	27.29%	25.52%

Figure 20: Summary of Variance Decomposition

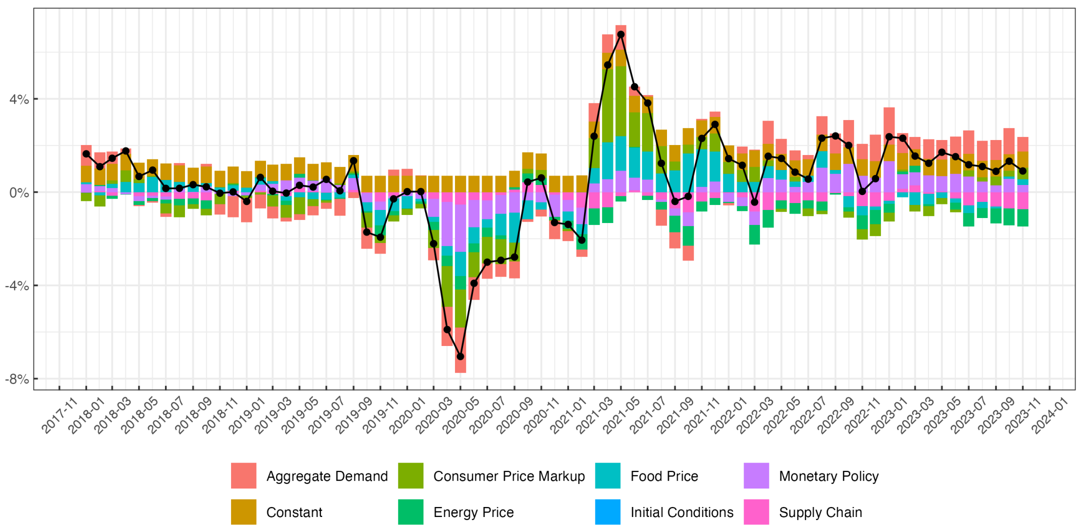
3.4 Historical Decomposition

Variance decomposition provides an explanation of the contribution of each shock to the variance of the variable, while historical decomposition directly calculates the quantitative contribution of each shock to the historical realized values of the variable. Next, explanations will be provided for historical decomposition. Although historical decompositions are calculated for the entire sample period from January 1998 to November 2023, this paper focuses on the period from January 2018 to the November 2023, particularly during the progression of the COVID-19 pandemic and the Russian invasion of Ukraine. We obtained historical decomposition data for price variables (CPI and PPI) and output variables (GDP and CON) from four different models and plotted them as Figures 21, 22, 23 and 24.

It can be observed that from January 2018 to November 2023, the effect of supply chain shock on price variables (CPI and PPI) has consistently been positive, while its effect on output variables (GDP and CON) has been mostly negative during this period. This indicates that supply chain shocks have a promoting effect on prices but impose a constraining effect on output. Due to the impact of the pandemic, the effect of supply chain shock on prices was particularly significant from early 2021 to the end of 2022. From Figure 21 and Figure 22, it can be observed that during the period from early 2020 to the end of 2021, amid the pandemic, consumption activities were suppressed, and the impact of aggregate demand shock on consumer prices was negative. However, since 2022, with the stabilization of the pandemic and the recovery of demand, aggregate demand shock has played a boosting role in driving price increases. Indeed, a similar phenomenon can also be observed regarding GDP and consumption. Throughout the entire year of 2020, the impact of aggregate demand shock on GDP and consumption was negative. However, starting from 2021, the aggregate demand shock began to turn positive. The estimated results of aggregate demand shock are consistent with the economic and social situation at that time. In the early stages of the pandemic, influenced by panic and various pandemic policies, demand plummeted significantly. But as the pandemic stabilized and socio-economic activities resumed, aggregate demand gradually rebounded, further promoting economic recovery.

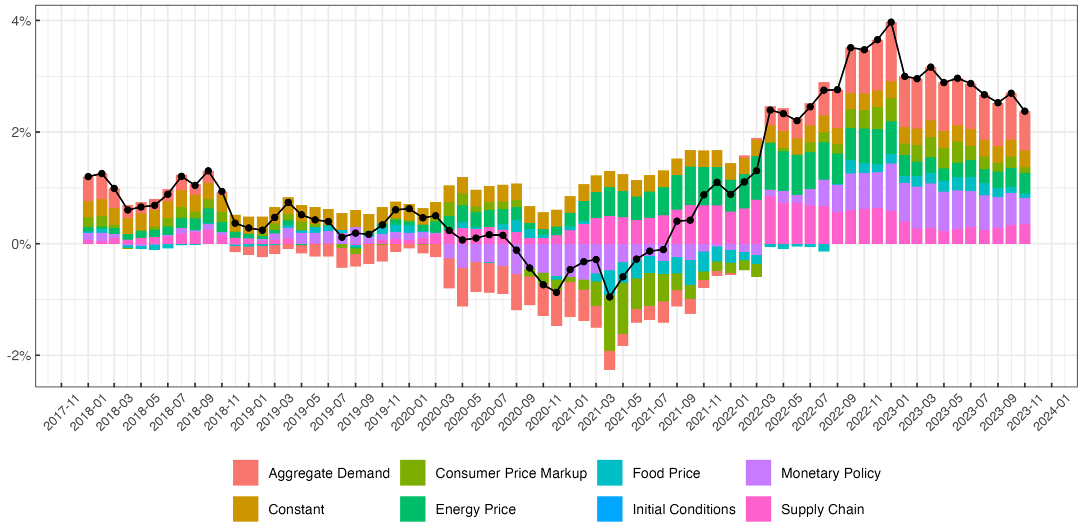


(a) Historical Decomposition of CPI

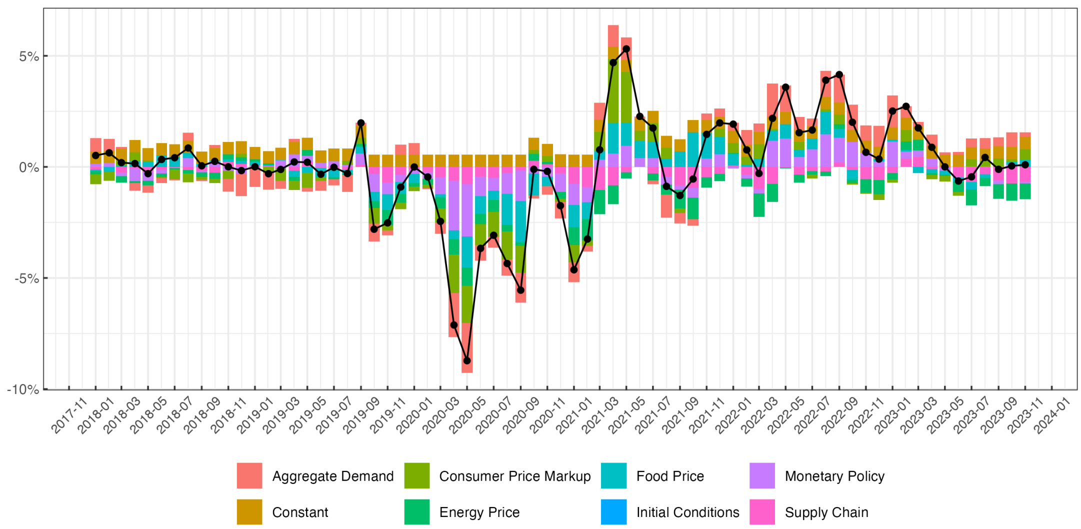


(b) Historical Decomposition of GDP

Figure 21: Historical Decomposition CPI-GDP-version model

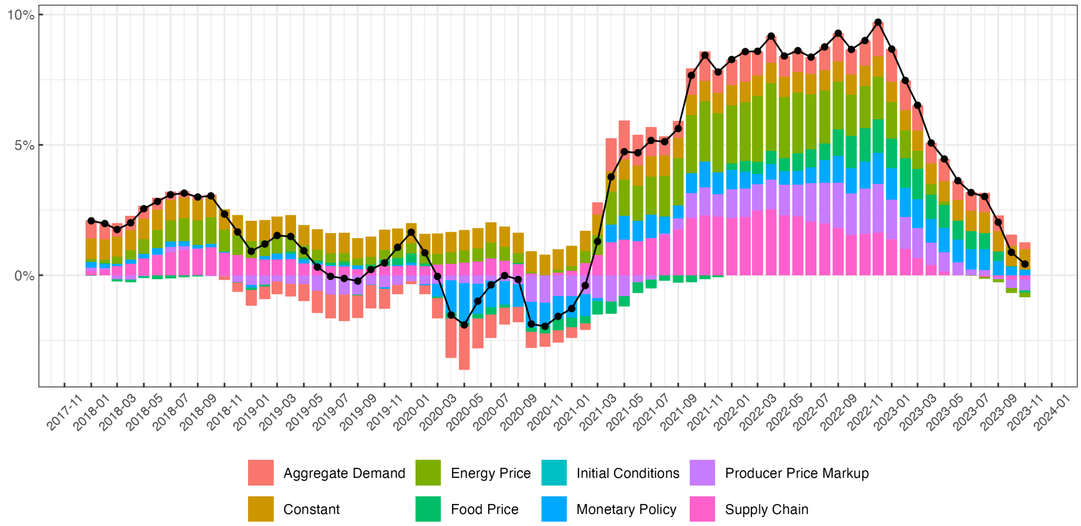


(a) Historical Decomposition of CPI

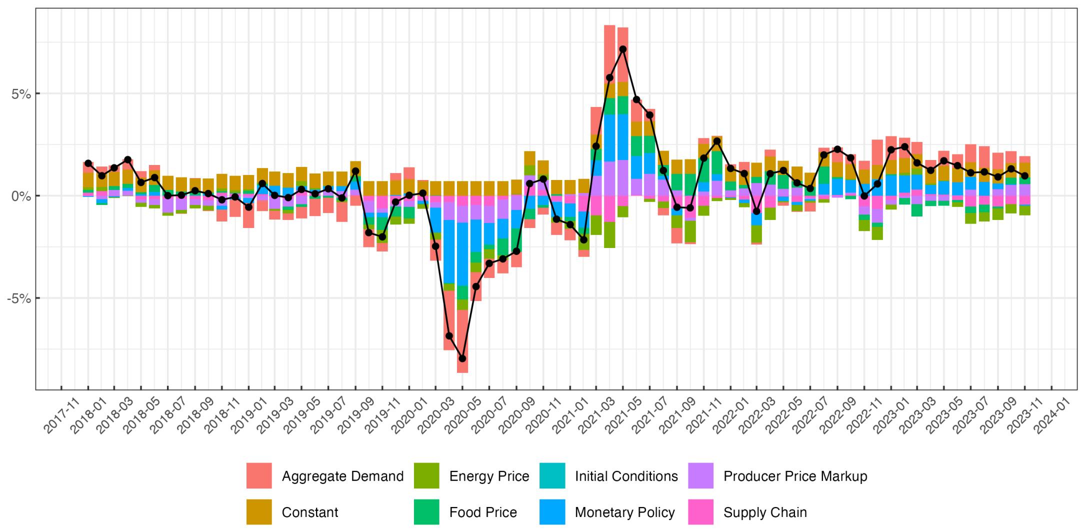


(b) Historical Decomposition of Consumption

Figure 22: Historical Decomposition CPI-CON-version model

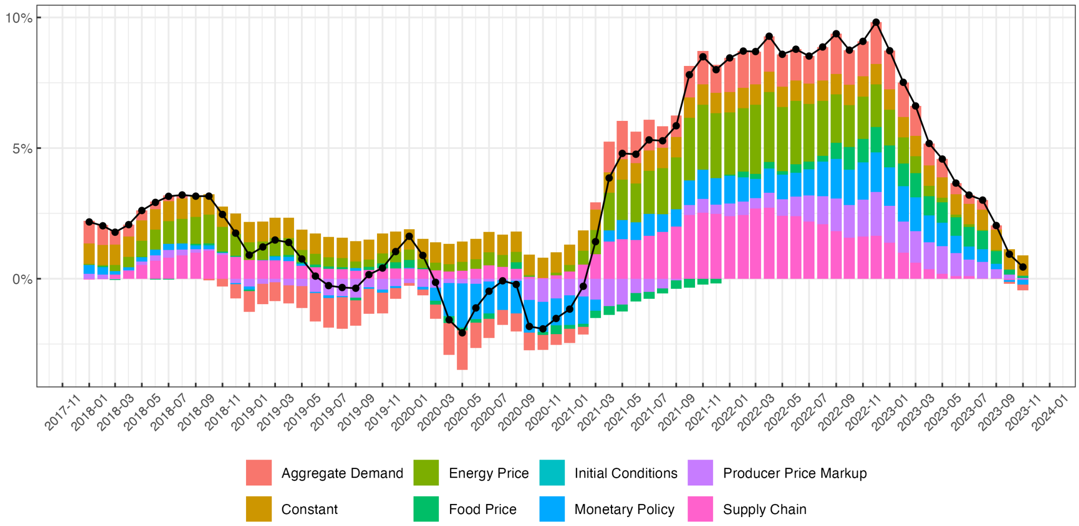


(a) Historical Decomposition of PPI

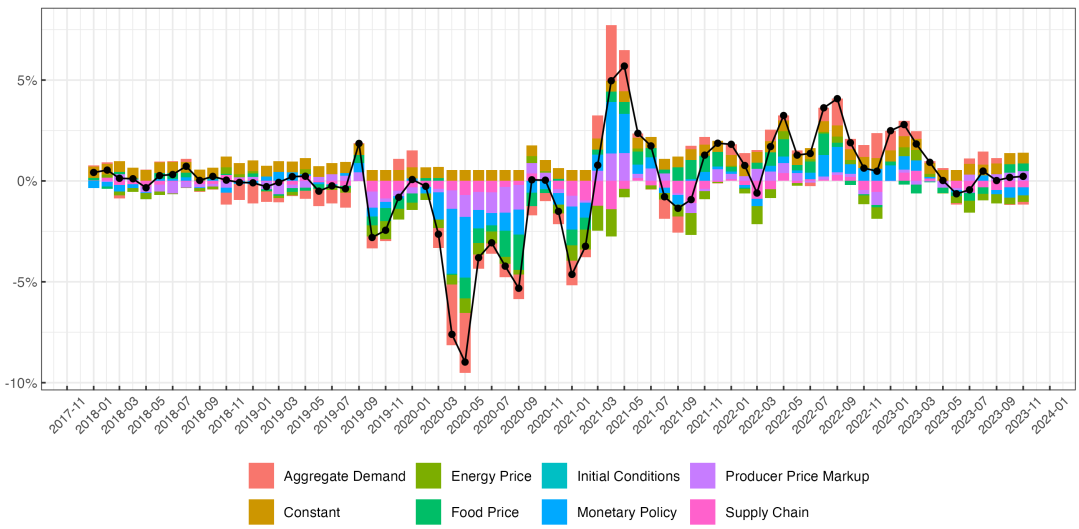


(b) Historical Decomposition of GDP

Figure 23: Historical Decomposition PPI-GDP-version model



(a) Historical Decomposition of PPI



(b) Historical Decomposition of Consumption

Figure 24: Historical Decomposition PPI-CON-version model

The explanation above also holds true when considering Figures 23 and 24. The historical decomposition of the two model estimated using PPI data reveals that supply chain shock had a predominantly positive impact on producer prices from early 2018 to early 2023. In other words, supply chain shock consistently exerted a positive influence on producer prices throughout the majority of this period. However, starting from 2023, the impact of supply chain shock on producer prices is nearly absent, while it continues to affect consumer prices. The estimated values of consumer/producer price markup shock, energy price shock and food price shock within the sample period are also consistent with our understanding of the socio-economic situation at that time. Finally, let's examine the impact of monetary policy shock on prices and output.

Firstly, starting from March 2022, identified monetary policy shocks have had a stimulating effect on consumer prices. Even earlier, from March 2021, the identified monetary policy shocks have also had a positive effect on producer prices. However, overall, the impact of monetary policy shocks on consumer prices is greater. Faced with the inflation during the later-stage of pandemic, the Bank of Japan did not respond to the increasing inflation by raising interest rates as the Federal Reserve did. Instead, it maintained its relative easing monetary policy, which to some extent allowed inflation to rise. Additionally, central banks primarily focus on consumer prices, and monetary policy adjustments are not necessarily targeted at producer prices. Therefore, the impact of monetary policy on producer prices is relatively weak. For output variables (GDP and CON), while identified monetary policy shocks during the sample period exhibit both positive and negative effects, for the most part, monetary policy shocks have had a positive impact on GDP and consumption. This is consistent with the easing policy stance consistently maintained by the Bank of Japan.

In conclusion, through variance decomposition and historical decomposition, this paper analyzes how each structural shock affects the fluctuations in economic variables. Of course, the empirical results in this paper are based on the data and shock identification method used, and it is expected that the results would change with different data and identification methods. Through estimating four models by combining two types of price data (CPI and PPI) and two types of output data (GDP and CON), we compared and analyzed the impacts of six shocks on the macroeconomic fluctuations. Overall, despite the slight differences in the quantitative results obtained from different models, the interpretations of the results are essentially consistent through variance decomposition and historical decomposition. This means that our identification strategy is robust, and the empirical results are reasonably convincing.

4 Concluding Remarks and Policy Implications

During the past three years, marked by the simultaneous progression of the COVID-19 pandemic and the Russian invasion of Ukraine, global disruptions in supply chains and soaring energy and food prices have occurred. Given the advancement of modern economic activities characterized by highly specialized and efficient division of labor, the smooth functioning of supply chains is considered a fundamental condition for economic activities. However, the vulnerability of supply chains to infectious diseases, natural disasters, and geopolitical conflicts has been frequently highlighted. Understanding the impact of supply chains on economic activities is of paramount importance. Based on this awareness, this paper estimates local projection and a structural VAR model with sign restrictions using data on the Global Supply Chain Price Index (GSCPI) and other macroeconomic variables to examine the effects of economic shocks such as supply chain shocks and energy and food price shocks on the recent Japanese economy. The use of the GSCPI data in this paper represents a novel empirical analysis targeting the Japanese economy. Moreover, the analytical results obtained in this paper are highly explanatory, consistent with the perception of socioeconomic conditions at the time, and reasonably robust.

Combining the conclusions above, let's discuss how to address the macroeconomic impact of supply chain disruptions from the perspective of monetary policy. Although the conclusions of this paper are not based on rigorous theoretical economic models and do not offer normative policy recommendations from the perspective of orthodox economic analysis, the empirical analysis results still provide some reference value. Firstly, inflation caused by supply chain disruptions tends to persist for a considerable period. Therefore, it is necessary for central banks to anticipate inflation and adjust monetary policy in a timely manner once supply chain tightness is detected. Monitoring indices such as the GSCPI can serve as a powerful reference for central banks when implementing monetary policy. Based on the conclusions from the empirical analysis in this paper, because inflation caused by supply chain disruptions is unlikely to dissipate quickly, it may be wise for central banks to swiftly tighten monetary policy once inflation caused by supply chain disruptions is observed, thereby suppressing inflation and curbing the formation of inflation expectations. Some argue that the Federal Reserve misjudged price trends, as its phased policy rate hikes since 2022 have not effectively curbed the rise in US inflation. Since entering 2024, the inflation data released in recent months have consistently exceeded market expectations. Once inflation expectations are formed, it is challenging to quickly restore public expectations of inflation to a low and stable level in the short term. As a result, stimulating the real economy through interest rate cuts becomes difficult, as such measures may exacerbate inflation expectations, leading to a dilemma.

It should be noted that the conclusions drawn in this paper are based on time-series methods and should be interpreted only within the context of the empirical model. Mainstream dynamic macroeconomic models typically do not account for the heterogeneity of firms, thus lacking specifications that incorporate the complex network structure of supply chains. While input-output analysis based on industry input-output tables is often used as a method to incorporate supply chains into macroeconomic models, these tables provide static statistical data that may not necessarily replicate the structure of supply chains. Recently, research has advanced in visualizing the structure of supply chains and elucidating how shocks propagate along supply chains based on the methodology of network science, rather than traditional economic methods such as time-series analysis. In the future, it is expected that the role of supply chains in economic activities will be further elucidated by combining traditional empirical analysis methods with new approaches.

References

[1] Benigno, G., Di Giovanni, J., Groen, J. J., & Noble, A. I. (2022). The GSCPI: A New Barometer of Global Supply Chain Pressures. FRB of New York Staff Report, (1017).

[2] Jordà, Ò. (2005). Estimation and Inference of Impulse Responses by Local Projections. American Economic Review, 95(1), 161-182.

[3] Finck, D., & Tillmann, P. (2022). The Macroeconomic Effects of Global Supply Chain Disruptions (No. 14/2022). Bank of Finland Institute for Emerging Economies (BOFIT).

[4] Bolhuis, M. A., Hakobyan, S., & Andriantomanga, Z. (2023). Global Supply Chain Disruptions: Challenges for Inflation and Monetary Policy in Sub-Saharan Africa (No. 2023/039). International Monetary Fund.

[5] Kabaca, S., & Tuzcuoglu, K. (2023). Supply Drivers of the US Inflation Since the Pandemic (No. 23-19). Bank of Canada.

[6] Kliesen, K. L., & Werner, D. (2022). Using Beige Book Text Analysis to Measure Supply Chain Disruptions. Economic Synopses, (18), 1-2.

[7] Soto, P. E. (2023). Measurement and Effects of Supply Chain Bottlenecks Using Natural Language Processing (No. 2023-02-06). Board of Governors of the Federal Reserve System (US).

[8] Primiceri, G. E. (2005). Time Varying Structural Vector Autoregressions and Monetary Policy. The Review of Economic Studies, 72(3), 821-852.

[9] Zanetti, F., Bai, X., Fernández-Villaverde, J., & Li, Y. (2024). The Causal Effects of Global Supply Chain Disruptions on Macroeconomic Outcomes: Evidence and Theory. CIGS Working Paper Series, (24-003E).

[10] Krippner, L. (2020). A Note of Caution on Shadow Rate Estimates. Journal of Money, Credit and Banking, 52(4), 951-962.

[11] Wang, R. (2019a). Unconventional Monetary Policy in Japan: Empirical Evidence from Estimated Shadow Rate DSGE Model. Journal of International Commerce, Economics and Policy, 10(02), 1950007.

[12] Wang, R. (2019b). Estimating the Monetary Policy Measures of Japan in Shadow/ZLB Term Structure Model. Applied Economics and Finance, 6(6), 126-139.

[13] Montiel Olea, J. L., & Plagborg-Moller, M. (2021). Local Projection Inference is Simpler and More Robust than You Think. Econometrica, 89(4), 1789-1823.

[14] Plagborg-Moller, M., & Wolf, C. K. (2021). Local Projections and VARs Estimate the Same Impulse Responses. Econometrica, 89(2), 955-980.

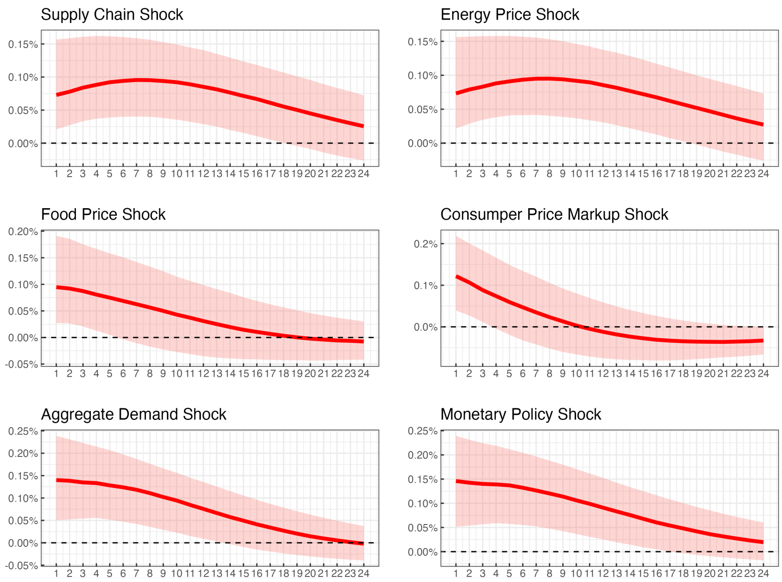
[15] Uhlig, H. (2005). What are the Effects of Monetary Policy on Output? Results from An Agnostic Identification Procedure. Journal of Monetary Economics, 52(2), 381-419.

[16] Arias, J. E., Rubio-Ramírez, J. F., & Waggoner, D. F. (2018). Inference based on Structural Vector Autoregressions Identified with Sign and Zero Restrictions: Theory and Applications. Econometrica, 86(2), 685-720.

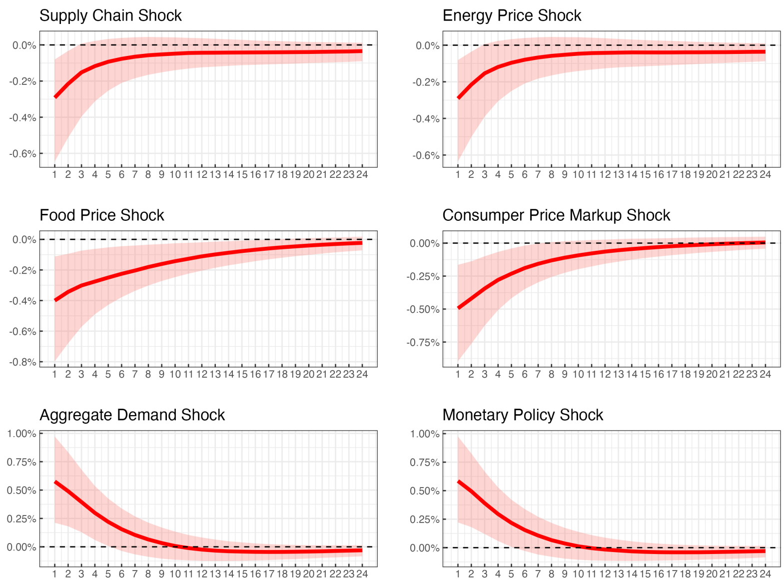
[17] Rubio-Ramirez, J. F., Waggoner, D. F., & Zha, T. (2010). Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference. The Review of Economic Studies, 77(2), 665-696.

[18] Smets, F., & Wouters, R. (2007). Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach. American Economic Review, 97(3), 586-606.

Appendix: Impulse Response of Structural VAR

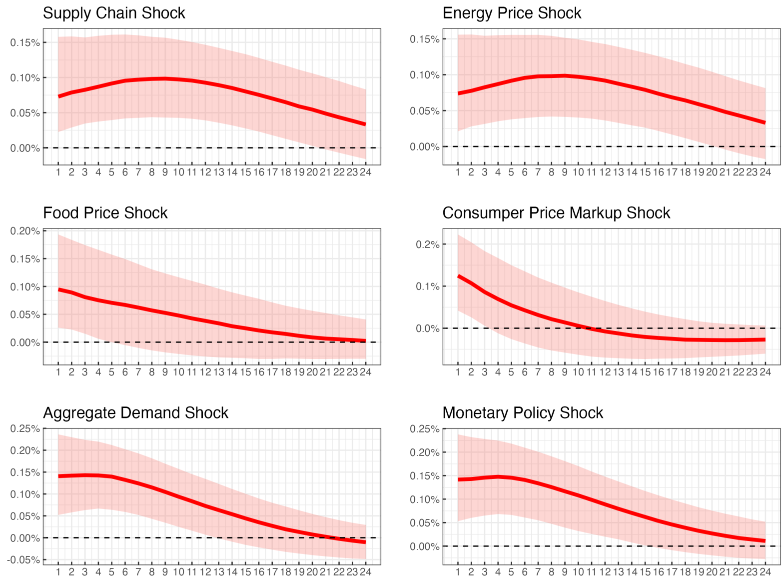


(a) Impulse Response of CPI

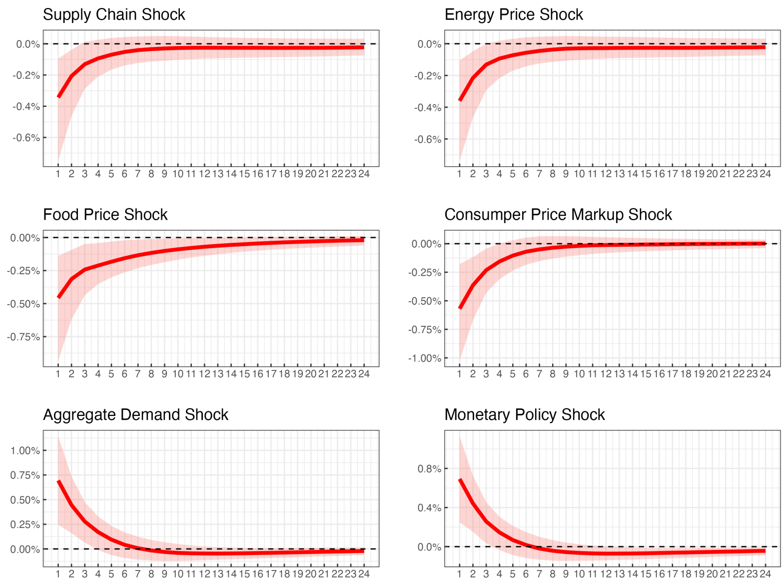


(b) Impulse Response of GDP

Figure 25: Impulse Response of CPI-GDP-version model

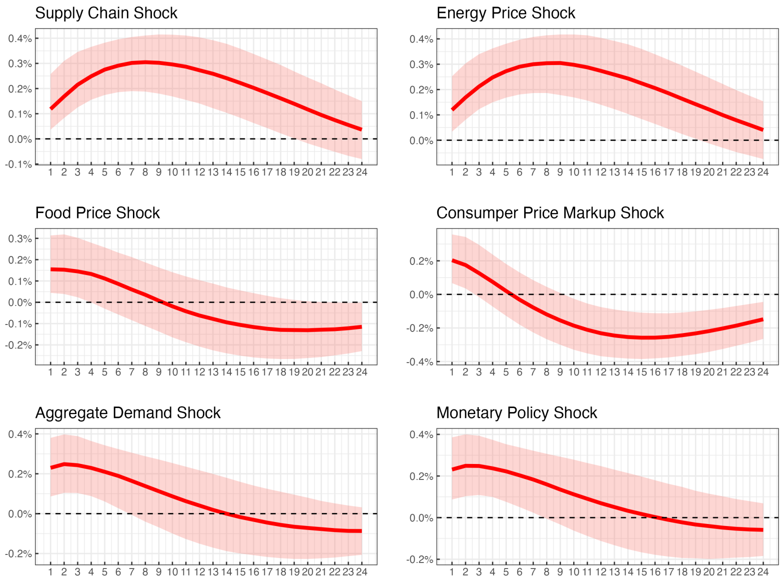


(a) Impulse Response of CPI

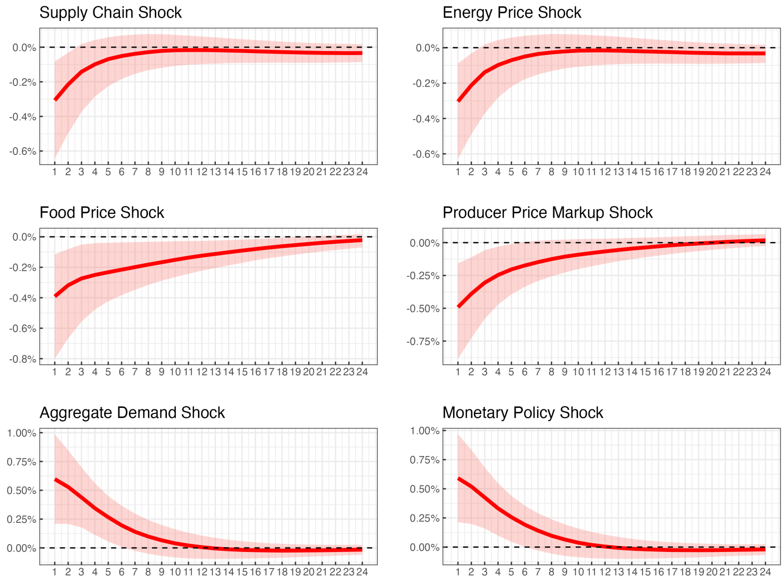


(b) Impulse Response of Consumption

Figure 26: Impulse Response of CPI-CON-version model

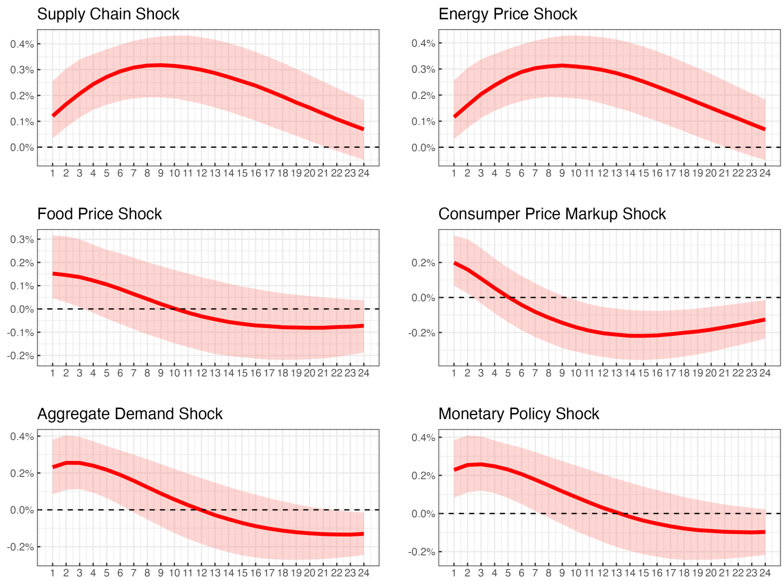


(a) Impulse Response of PPI

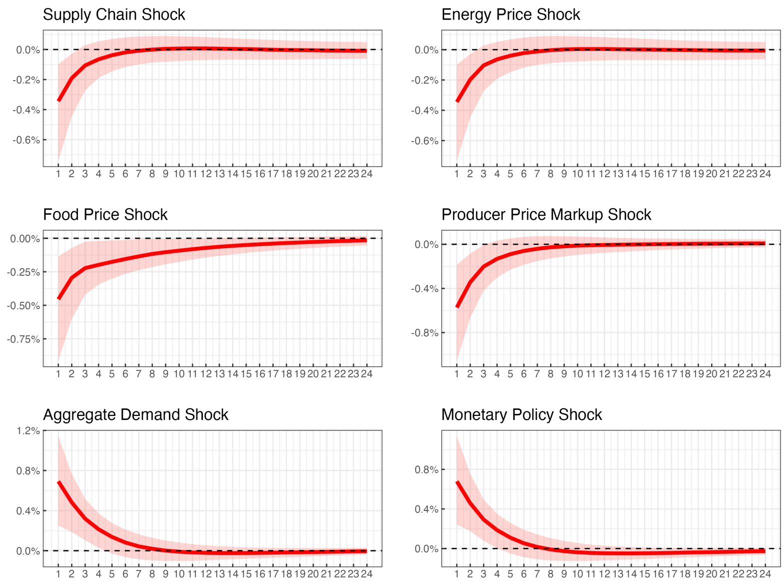


(b) Impulse Response of GDP

Figure 27: Impulse Response of PPI-GDP-version model



(a) Impulse Response of PPI



(b) Impulse Response of Consumption

Figure 28: Impulse Response of PPI-CON-version model