Do Supply Chain Disruptions Matter for Global Economic Conditions? ★

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Abstract

The COVID-19 pandemic and its aftermath exposed the vulnerabilities of global supply chains, leading to widespread delays and shortages that highlighted the interconnectedness of economies. This paper examines the global impact of supply chain disruptions on economic conditions, drawing on literature related to economic uncertainty, global economic integration, and the global supply chain disruptions. Using a Bayesian Vector Autoregression (BVAR) model, we analyze the effect of supply chain shocks. The empirical findings reveal that these disruptions significantly influence global economic stability, particularly through their impact on aggregate inflation and the policy responses that accompanies them.

Keywords: Supply Chain, Business Cycles, and Global Economic Uncertainty.
JEL: E31, E32, D24

Highlights

- Supply chain disruptions transmit a world disturbance to the business cycle.
- Empirical findings indicate that supply chain pressures are an important driver of economic policy uncertainty.
- Supply chain disruptions have significant effects on global economic stability, particularly influencing inflation.
- Empirical results show that supply chain disruptions are a key factor driving the increase in policy responses from most central banks during the post-pandemic period.

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1. Introduction

The COVID-19 pandemic and its aftermath exposed and exacerbated vulnerabilities within the global economy. Among the most critical challenges has been the severe disruption of global supply chains. These disruptions, initially triggered by factory closures, lock-downs and mobility restrictions, caused considerable delays and shortages in the production and distribution of goods. As economies began to recover, the situation became more complex, with the resurgence in demand quickly outpacing the constrained supply. This imbalance not only highlighted the fragility of global supply networks but also underscored the profound inter-connectedness of modern economies, where disruptions can have cascading effects globally.

In a world where economic activities are increasingly intertwined, disruptions to global supply chains pose significant risks to economic stability. The interdependence of economies means that shocks can rapidly propagate across borders, affecting production, trade, and financial markets worldwide. This phenomenon has been observed during the pandemic, where disruptions had far-reaching implications, amplifying economic volatility and uncertainty. Understanding these dynamics is crucial for policymakers and informing the general public, as it provides insights into the vulnerabilities of the global economic system and the potential for future shocks to disrupt global stability.

This paper seeks to explore the global dimensions of supply chain disruptions and their implications for economic conditions. Our analysis is grounded in three distinct strands of literature, each of which provides a framework for understanding the complex interactions between supply chain pressures and the broader economy.

The first strand of literature addresses the concept of global economic integration and its implications for business cycle synchronization. Numerous papers find evidence of a world business cycle (e.g., Kose et al., 2003, Monfort et al., 2003, Ciccarelli and Mojon, 2010, Ginn, 2023*a*, Ginn, 2023*b*), where economic activities in different countries are increasingly synchronized due to globalization. The implications of global integration are profound, as it suggests that shocks can have immediate and significant impacts on other regions, further amplifying the effects of global supply chain disruptions.

The second strand of literature focuses on economic uncertainty and its relationship with economic conditions. Recent research has explored the role of oil prices in generating economic uncertainty, particularly through the lens of Economic Policy Uncertainty (EPU), a measure developed by Baker et al. (2016). EPU is negatively correlated with the business cycle (e.g., Bloom, 2009 and Baker et al., 2016). The broader implications of economic uncertainty are significant, as it affects firm-investmentment (e.g., Kang et al., 2014, Handley and Limao, 2015), stock prices (e.g., Kang and Ratti, 2013*a*, Antonakakis et al., 2013, You et al., 2017, Ginn, 2023*a*), bank valuation (He and Niu, 2018) and unemployment (e.g., Caggiano et al., 2014, Caggiano et al., 2017). Ginn (2022) finds that natural disasters, which can be considered exogenous shocks similar to supply chain disruptions, can also lead to increased aggregate uncertainty, underscoring the need to understand how such disruptions can spill over into broader economic instability. Studies such as Kang and Ratti (2013*b*), Antonakakis et al. (2014), Hailemariam et al. (2019) and Dufrénot et al. (2024) examine the transmission mechanisms through which international oil prices can create spillover effects on domestic economies, thereby increasing uncertainty.

The third strand, and the focus of our contribution, relates to global supply chain disruptions. Numerous studies have established a link between these disruptions and diminished financial performance. For instance, Hendricks and Singhal (2003) demonstrate that supply chain disruptions, such as production or shipping delays, can significantly reduce shareholder value. Hendricks and Singhal (2005*b*) show that such disruptions increase equity risk and lead to a decline in market value, while Hendricks and Singhal (2005*a*) find that supply chain issues negatively impact a firm's financial health by lowering revenue and operating income, increasing costs, and raising total inventory levels. Notably, affected firms may take up to two years to fully recover from the financial damage. Similarly, Baghersad and Zobel (2021) report that supply chain disruptions are associated with reduced operating income, returns on sales and assets, as well as poor performance in total asset turnover. The Global Supply Chain Pressure Index (GSCPI) provides a novel, comprehensive measure of global supply chain disruptions (Benigno et al., 2022). Recent studies have identified supply chain pressures as key drivers of inflation, particularly in the Euro area (Ascari et al., 2024), the US (Diaz et al., 2023, Ginn and Saadaoui, 2024) and in relation to geopolitical risks (Asadollah et al., 2024). When supply chains are strained—due to factors such as shipping delays, shortages of key inputs, or rising transportation costs—businesses face heightened uncertainty regarding production schedules, costs, and revenues. This increases economic uncertainty, particularly when disruptions are prolonged. In addition, rising supply chain pressures contribute to higher inflation due to supply shortages and escalating costs. As the GSCPI increases, central banks may be forced to tighten monetary policy, which introduces uncertainty regarding the future course of inflation control measures. This uncertainty can raise Economic Policy Uncertainty (EPU), especially as policymakers react to supply-side challenges. Furthermore, global supply chain pressures often intersect with geopolitical risks, such as trade wars, tensions along key shipping routes, or dependency on goods from politically unstable regions. Consequently, a rise in the GSCPI may signal growing geopolitical tensions, further increasing EPU as governments adapt trade, security, and foreign policies to mitigate these risks.

In this paper, we contribute to the literature on the economic impacts of global supply chain disruptions by estimating a Bayesian Vector Autoregression (BVAR) model at the global level, with a particular emphasis on their effects on the world business cycle. Given the global nature of these disruptions, their consequences extend beyond individual countries, having broad implications for the entire global economy. Using monthly data from January 1999 to June 2024 at the global level, we analyze the transmission of global supply chain shocks across interconnected economies.

Unlike prior studies, which employ country-specific models, our global modeling approach facilitates an empirical framework to estimate how supply chain disruptions propagate through the global economy. This approach also enables us to explain post-pandemic inflation dynamics and the subsequent interest rate responses, which in turn influence economic policy uncertainty. The findings underscore the significant global risks these disruptions pose, providing novel evidence that policymakers must consider the international dimensions of supply chain pressures when crafting economic policies to mitigate their adverse effects.

The rest of the paper is structured as follows: in Section 2 describes the data. Section 3 discusses the modelling methodology and empirical results. Section 4 concludes the paper, to include policy recommendations.

2. Data

The model is based on monthly data spanning from 1999:JAN to 2024:JUN covering key macroeconomic variable types. The variables included in our analysis include economic uncertainty, output (industrial production), aggregate consumer price (CPI), global supply chain pressure index (GSCPI) and global economic policy uncertainty (GEPU). The data is summarized in Table 1.

Table 1: Variable Selection

Item	Symbol	Source	Description
Output	$\ln Y_t$	OECD	Global Production Index
Aggregate CPI	$\ln P_t$	OECD	Global Price Index
Interest Rate	R_t	OECD/FRED	Interest rate
Supply chain shock	$GSCPI_t$	Federal Reserve of NY	GSCPI
Economic Uncertainty	$\ln EPU_t$	FRED	GEPU
Recession Dummy	δ_t	FRED	OECD Recession Dates (OECDNMERECM)

Growth variables are defined as 100 times the log-difference (year-on-year). Six global variables are considered: GEPU, output, aggregate inflation, interest rate and GSCPI. Each variable is discussed in turn.

2.1. Global EPU

Building on the EPU index by Baker et al. (2016), Davis (2016) constructs a measure of GEPU. GEPU is considered in the empirical analysis. EPU is negatively correlated with the business cycle (e.g., Bloom, 2009 and Baker et al., 2016).

2.2. Construction of GDP Weighted Global Aggregates

Following Dufrénot et al. (2023) and Ginn (2024), we construct three global economic indicators based on twenty-two sampled economies[1] using a GDP weighted index. The global indicators include output (industrial production) growth[2], output gap[3], aggregate inflation and the interest rate[4]. The weight of each economy in the index is derived from its economic size (proxied using annual GDP data based on puchasing power parity ("PPP")), which is accordingly rebased (i.e., sums to one for each period). We then apply the weights to each of the respective global indicators in the respective period, considering the data is monthly. For consistency, the aggregate price (CPI) is seasonally adjusted via ARIMA X-12 algorithm from the U.S. Census Bureau.

In the Appendix, Figure 9 plots the period-to-period movements, which are quite stable where the relationship evolves over a longer period of time. The international data for the twenty-two economies and world data index is plotted in the Appendix (see Figure 9) and are used to represent international economic conditions (henceforth, "WORLD").

2.3. Global Supply Chains

Global supply chain pressure index ($GSCPI_t$) is obtained from Benigno et al. (2022).

[1]Based on IMF data, the twenty-two economies considered in this paper represent 75.2% of global output in purchasing power parity (PPP) GDP, see e.g. `https://www.imf.org/external/datamapper/PPPGDP@WEO`. The twenty-two economies include: Brazil ("BRA"), Canada ("CAN"), Switzerland ("CHE"), Chile ("CHL"), China ("CHN"), Columbia ("COL"), Czech Republic ("CZE"), Denmark ("DNK"), Euro zone (19 countries; "EUR"), United Kingdom ("GBR"), Hungary ("HUN"), India ("IND"), Israel ("ISR"), Japan ("JPN"), Mexico ("MEX"), Norway ("NOR"), South Korea ("KOR"), Poland ("POL"), Russia ("RUS"), Sweden ("SWE"), Turkey ("TUR") and the United States ("USA"). The Euro zone values are based on the 19 member countries (i.e., Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain).

[2]For India, manufacturing production index (FRED mnemonic INDPRMNTO01IXOBM) is used as opposed to total production index (FRED mnemonic INDPROINDMISMEI), considering data availability (the correlation is 0.9918 for Jan 2000 to Dec 2018). For China, we use total production excluding construction (FRED mnemonic CHNPRINTO01IXPYM). As the production index for China includes missing values, the Kalman smoother using an ARIMA state space representation is used to impute missing values.

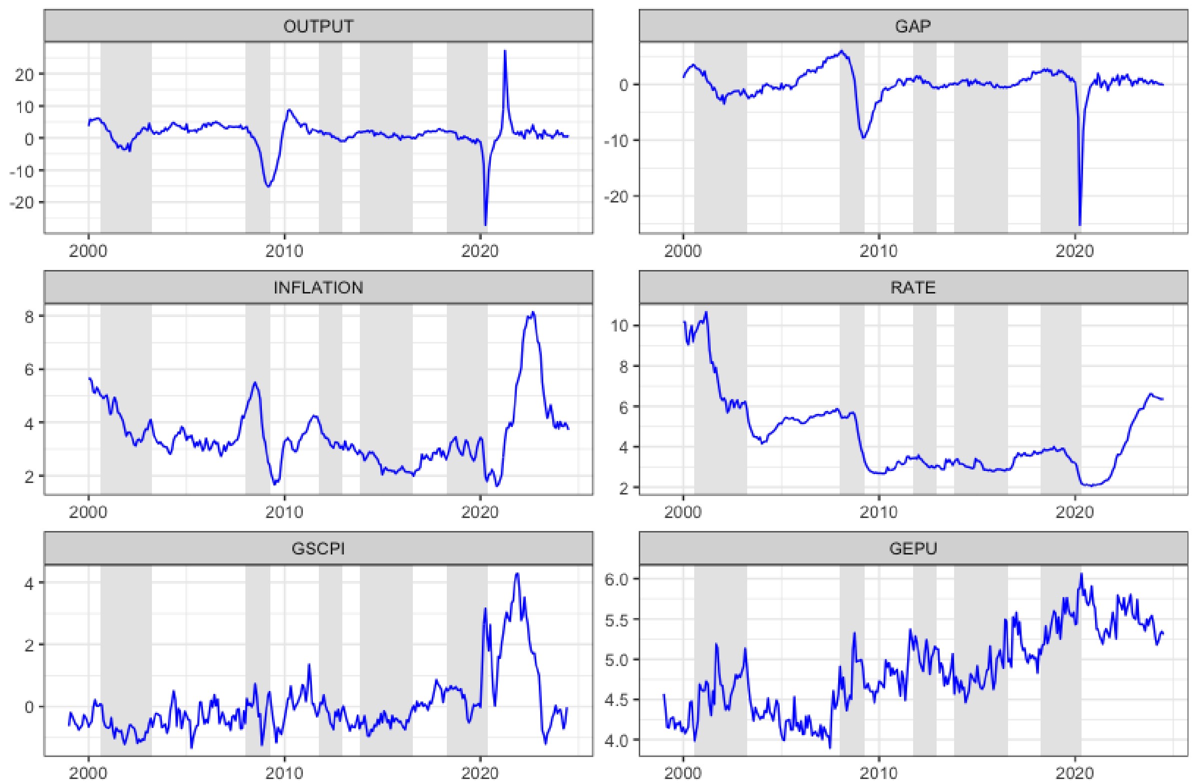
[3]The cyclical component of the OECD production index is estimated by HP filter. The HP filter is used to detrend the data into a cyclical stationary component (Hodrick and Prescott, 1997). The trend is based on λ = 129,600, a standard value for data at monthly frequency (see e.g. Ravn and Uhlig (2002))

[4]For India, the interest rate is based on the 90 day Treasury Bill interest rate (e.g., Patnaik et al., 2011, Gabriel et al., 2012, Saxegaard et al., 2010, Anand et al., 2014, Ginn and Pourroy, 2020).

2.4. *Global Variables*

Figure 1 plots the global data which shows the global dataset captures two major turning points. The top-pane shows a sizable decline in output growth and the output gap, which occurred during the Global Financial Crisis (GFC)[5] and onset of the spread of the COVID-19 virus. There was a noticeable decrease in aggregate inflation and interest rate during these two time periods, albeit inflation aggregate inflation increased almost in parallel with the rise in GSCPI, corresponding with an in interest rates.

Figure 1: Global Economic Data



Shaded areas indicate OECD recession dates.

3. Methodology and Results

We estimate the dynamic responses from the endogenous variables, we estimate the Bayesian Vector Autoregression (BVAR) model using sign restrictions. While the BVAR model is well-suited for analyzing the dynamic relationships among macroeconomic variables, our knowledge of how GSCPI directly impacts GEPU is limited. Initially, we estimate how GSCPI influences GEPU, while controlling for other factors, using both General Method of Moments (GMM) and Generalized Additive Models (GAM).

[5] According to the NBER, the recession dates for the U.S. is between 2007:DEC to 2009:JUN.

3.1. *Determinants of Global EPU*

Given the potential bidirectional causality between GEPU and other macroeconomic conditions, we turn to a General Method of Moments (GMM) and General Additive Model (GAM) to further explore the specific effect of GSCPI on GEPU.

We incorporate a GMM approach to address potential endogeneity concerns that arise from this bidirectional relationship. Unlike Ordinary Least Squares (OLS), which assumes exogeneity of the explanatory variables, GMM allows for the use of lagged control variables to account for endogeneity, thereby enhancing the reliability of the estimates. By utilizing lagged instruments, the GMM framework ensures a more robust treatment of the causal relationships between GSCPI, GEPU, and other economic variables.

Parallelly, we employ a GAM to explore the nonlinear interactions among variables without necessarily imposing restrictive parametric assumptions, *a priori*. This flexibility enables us to capture more complex dynamic relationships, especially when there are nonlinear effects between GSCPI and GEPU.

3.1.1. *GMM*

The GMM is formalized as follows:

$$\ln EPU_t = \alpha + \beta^T x_t + B(L)\Theta_t + u_t \tag{1}$$

where x_t is a vector of up to four control variables in the set $x_t = [\Delta\ln(Y_t), \Delta\ln(P_t), R_t, GSCPI_t]$, which includes output growth, aggregate inflation, interest rate and GSCPI data. Accordingly, we estimate two models, the first is based on output growth, inflation and interest rate ("M1"). The second model is based on the former and additionally includes GSCPI ("M2"). The model further includes an intercept (α), a vector of lagged control variables (Θ_t) and an error term (u_t). We set the lag operator (i.e., B(L)) of the control variables to 1. Accordingly, we estimate how economic conditions affect GEPU over the sample period. Table 2 demonstrates that GEPU is associated with lower output growth, higher inflation and lower interest rate consistent with the literature (e.g., Hailemariam et al., 2019, Ginn, 2022, Dufrénot et al., 2023, Dufrénot et al., 2024). We further find that GEPU increases in response to higher GSCPI. All coefficients in Table 2 are statistically significant.

Table 2: GMM Regression

	M1	**M2**
α	5.4849***	5.4224***
	(0.1541)	(0.1888)
β_Y	-0.0427***	-0.0403***
	(0.0061)	(0.0039)
β_P	0.2478***	0.1596***
	(0.0086)	(0.0116)
β_R	-0.4474***	-0.3240***
	(0.0340)	(0.0557)
β_{GSCPI}		0.1238***
		(0.0225)
AIC	256.1781	247.6558

Note: *, ** and *** denote significance at 10%, 5% and 1%, respectively.

The results for M1 and M2 suggests that GEPU is associated with lower output growth, higher inflation and lower interest rate. M2 demonstrates a positive relationship between GEPU and GSCPI. Table 3 demonstrates that coefficients are statistically significant. The Akaike Information Criterion (AIC) indicates that M2, which includes GSCPI, provides a better fit than M1.

3.1.2. GAM

We further explore the joint effect of economic variables impact GEPU via GAM. Specifically, we aim to account for potential non-linear interactions without imposing strong parametric assumptions on the functional form. The GAM model is specified as:

$$\ln EPU_t = \alpha + f_{Y,P,R,GSCPI}(\Delta\ln(Y_t), \Delta\ln(P_t), R_t, GSCPI_t) + \epsilon_t \quad (2)$$

The smooth term (i.e., $f_{Y,P,R,GSCPI}$) jointly models the relationship between the four variables on GEPU, accounting for their possible interactions and non-linear effects.

We further investigate whether there are interaction effects between the explanatory variables. The GAM framework allows us to relax the assumption of a linear response to the input variables.[6] The GAM can be formalized as follows:

Table 3: Empirical Results (GAM Regression)

Parametric coefficients:	Estimate	Std Error	t-value	p-value
α	4.843	0.0376	128.9	<0.01
Non-parametric coefficients:	EDF	REF.DF	F-value	p-value
$f_{Y,P,R,GSCPI}$	104.6	112.6	8.38	<0.01
Adjusted R^2	0.772			

Standard errors and reference degrees of freedom for the estimated terms are provided along with the t-value and F-value, respectively.

We estimate the interaction of a set of control variables as a tensor product (Wood et al., 2013). The GAM model allows for a set of basis functions for each marginal function for the interaction of variable combination $f_{Y,P,R,GSCPI}(\Delta\ln(Y_t), \Delta\ln(P_t), R_t, GSCPI_t)$.

Based on the estimated models, we provide a three-dimensional interaction surface plot of fitted values of $\ln GEPU_t$ (vertical axis) based on the explanatory variable combination (Breheny and Burchett, 2017). Figure 2 plots how the interaction terms influence GEPU. The left-pane indicates that higher GEPU tends to be associated with lower output growth and higher inflation, which can be characterized as a period of "stagflation". The middle-pane indicates that GEPU is higher during periods of low output growth and interest rate. The right-pane shows that GEPU tends to be highest when there is low output growth and high GSCPI.

In both the GMM and GAM analyses, the empirical findings show that GEPU is positively associated with GSCPI.

3.2. Bayesian Vector Autoregression Model

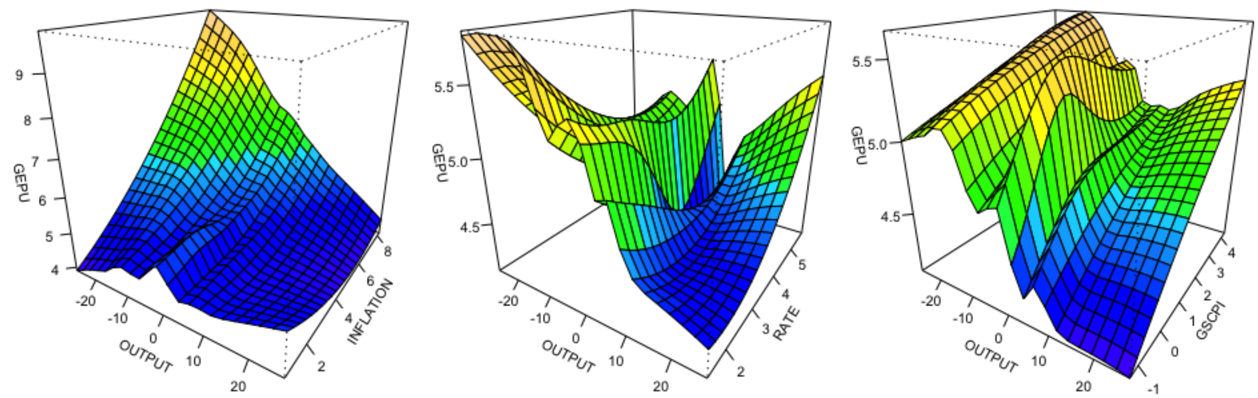
We employ a BVAR model to estimate the impact of global supply chain (GSCPI) shocks on global economic conditions. Following the methodologies of Giannone et al. (2015) and Kuschnig and Vashold (2021), the BVAR model is specified as follows:

$$y_t = \beta_0 + \mathbf{A}_1 y_{t-1} + ... + \mathbf{A}_p y_{t-p} + \epsilon_t, \epsilon_t \sim \mathcal{N}(0, \Sigma), t = \{1, ..., T\} \quad (3)$$

where y_t is a column vector of $(q \times 1)$ endogenous variables; β_0 is an intercept vector of $(q \times 1)$ terms; p is the lag length (based on Akaike information criterion of eleven lags); and ϵ_t is an error term of $(q \times q)$

[6]The model is estimated from the data without imposing a linear functional form, as in an OLS model.

Figure 2: Interaction Plots (GAM Regression)



with mean zero with variance-covariance matrix Σ. The BVAR is estimated using a Normal-Inverse-Wishart prior based on 50,000 simulations.

The vector of macroeconomic variables includes the following:

$$y_t^T = [GSCPI_t, \Delta \ln Y_t, \Delta \ln P_t, R_t, \ln GEPU_t] \quad (4)$$

where y_t^T is the transpose of a column vector that includes GSCPI, output growth, aggregate inflation, interest rate and GEPU. Identification is based on economic theory via sign restrictions.

GSCPI is ordered first in Equation 4 thereby assuming to be contemporaneously exogenous, followed by output growth, aggregate inflation and interest rate. Lastly, GEPU is ordered last (e.g., Colombo, 2013, Ginn, 2022, Dufrénot et al., 2024) to "purge" EPU from the contemporaneous effects on economic conditions (Colombo, 2013).

In this identification setup, we note that the interest rate response reflects the "collective stance" by major central banks (Ratti and Vespignani, 2016). The transmission of monetary policy remains equivocal insofar that policy responses are not necessarily coordinated. Domestic financial conditions can potentially become vulnerable global shocks, which can complicate monetary policy decision making (Kamin, 2010). While co-movement in domestic inflation rates may be related to cyclical fluctuations in the world economy, as Woodford (2007) shows that globalization does not impair the ability of central banks to control domestic inflation through national monetary policy.

3.2.1. IRFs and FEVD

To enhance the analysis of dynamic responses from endogenous variables, we utilize a BVAR model with sign restrictions, producing impulse response functions (IRFs) alongside 68% and 90% confidence bands and forecast error variance decomposition (FEVD). In the previous section, a main finding is that a global food price shock increases EPU.

Table 2 highlights that GEPU is associated with lower output growth, higher inflation, and lower interest rates, consistent with the literature (e.g., Hailemariam et al., 2019, Ginn, 2022, Dufrénot et al., 2023, Dufrénot et al., 2024). In the prior section (Section 3.1), we find a positive relationship between GSCPI and GEPU using two models (i.e., GMM and GAM) with statistically significant coefficients. The theoretical expectation that GEPU rises in response to heightened GSCPI is also supported by Ginn (2024), who shows that supply chain disruptions negatively affect real equity returns, as firms experience reduced profits and dividends. This relationship underscores the importance of considering GSCPI as a key driver of uncertainty. These empirical findings provide a strong basis for sign identification in the BVAR model.

An uncertainty shock is typically negatively related to the business cycle (e.g., Bloom, 2009, Baker et al., 2016). Meanwhile, aggregate demand shocks, characterized by unexpected increases in global real activity, tend to reduce uncertainty but increase inflation, prompting central banks to raise interest rates. On the supply side, cost-push shocks, which increase inflation while lowering output, also lead to higher interest rates. A GSCPI shock, reflecting global supply chain disruptions, mirrors a supply-side cost-push shock by raising uncertainty, reducing output, and increasing inflation and interest rates.

Recent studies (e.g., Diaz et al., 2023, Asadollah et al., 2024, Ascari et al., 2024, Ginn and Saadaoui, 2024) highlight the critical role that global supply chain pressures play in driving inflation and output reductions. Ascari et al. (2024) and Ginn and Saadaoui (2024) further show that GSCPI is a significant factor in Phillips curve estimations for both the euro area and the U.S., cementing its role in explaining inflation dynamics. Finally, a policy rate shock typically results in lower output and inflation.

Table 4: Identified Shocks

Response of	Shock				
	Global supply	Demand	Supply cost-push	Monetary policy	Uncertainty
Supply Chain Pressure (GSCPI)	+				
Output growth	-	+	-	-	
Aggregate inflation	+		+	-	
Policy rate	+	+	+	+	
Global EPU	+	-	+	-	+

The first column of Figure 3 shows that an uncertainty shock can reduce output. The second column shows that an aggregate demand shock reduces GEPU and puts upwards pressure on inflation and is associated with higher interest rate. A supply cost-push shock corresponds with a reduction in output and is inflationary. A supply chain shock raises global uncertainty by 0.1%, corresponding with a reduction (increase) in output (inflation) by circa 0.5% (0.1%). The shock to the interest rate corresponds with lower output and inflation.

The results of the FEVD are presented in Figure 4. The long-term effect of GSPCI (period 12) on output, aggregate inflation, the interest rate and GEPU is 3%, 20%, 2% and 4%, respectively.

3.2.2. Historical Decomposition

We provide the historical decomposition for output growth, aggregate inflation and the interest rate. Each is discussed in turn. The analysis is organized chronologically, covering key periods to highlight the impact of various shocks.

3.2.3. Pre-Global Financial Crisis (GFC)

The historical decomposition for output growth during the pre-GFC period shows relatively stable conditions with limited influence from global supply chain pressures (GSCPI). Shocks to global supply chain pressures had a mitigating effect on inflation, reducing inflationary pressures during this period. Output growth remained stable with minimal impact from global supply chain pressures. This period, commonly referred to as the "Great Moderation" (e.g., Galí and Gambetti, 2009, Bernanke, 2012), can be characterized by reduced volatility in economic activity and steady growth, indicating a period of relative economic stability.

Figure 3: BVAR IRFs (Baseline Model)

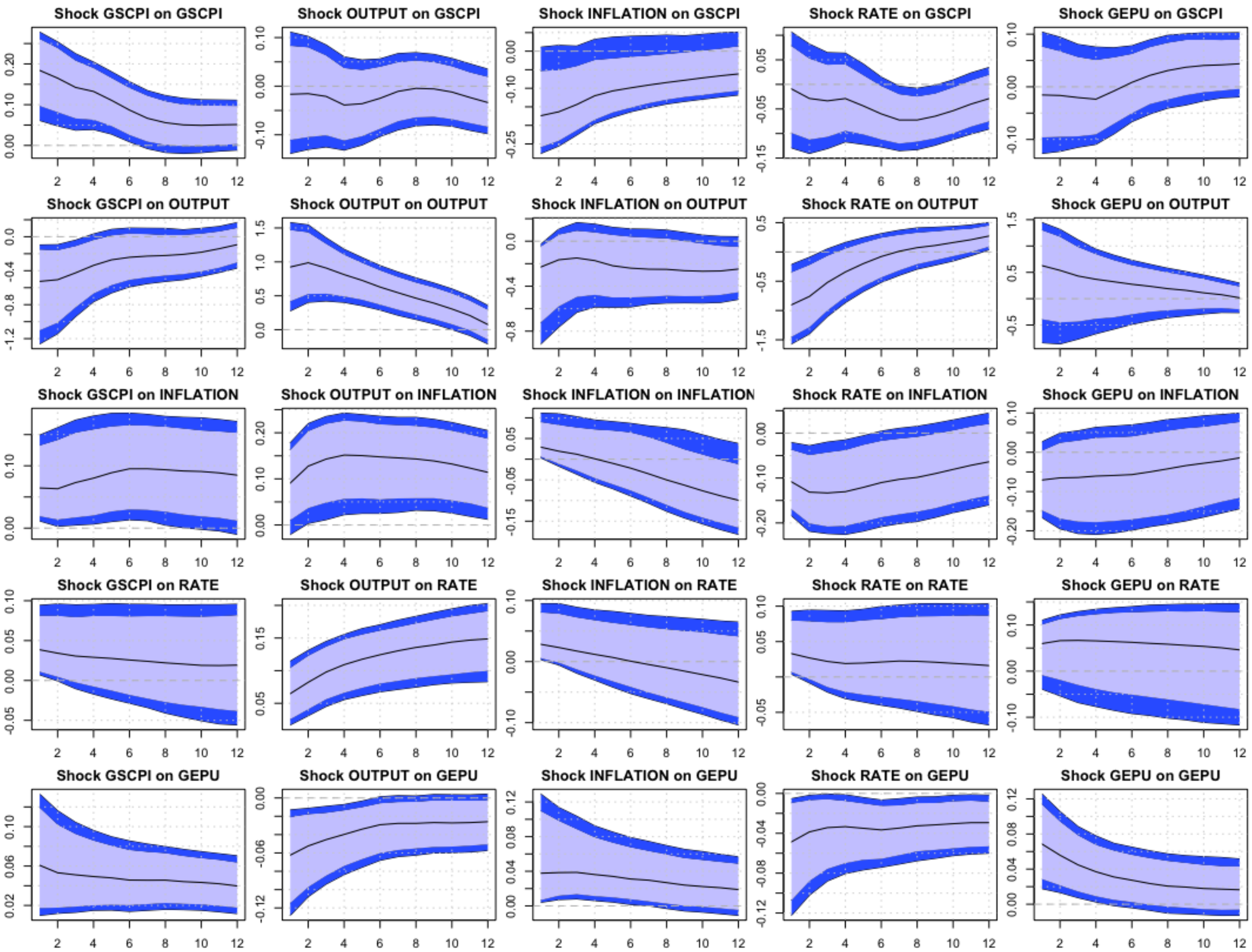


Figure 4: Variance Decomposition

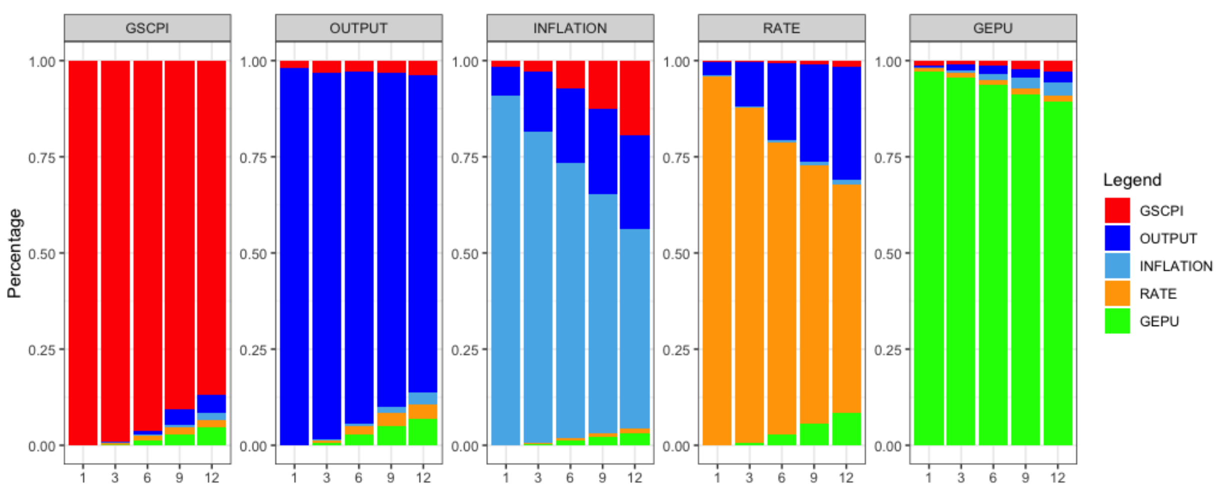
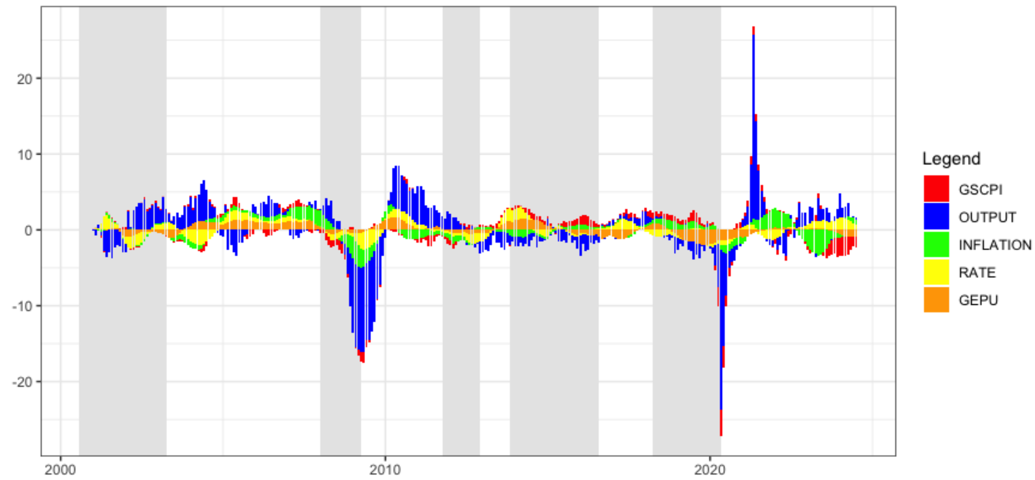
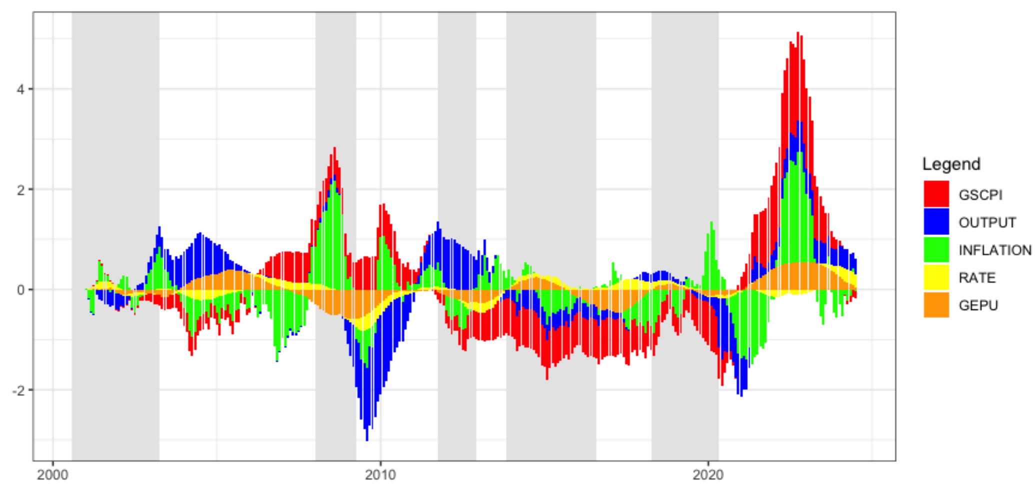


Figure 5: Historical Decomposition of Output



Shaded areas indicate OECD recession dates.

Figure 6: Historical Decomposition of Inflation



Shaded areas indicate OECD recession dates.

3.2.4. GFC

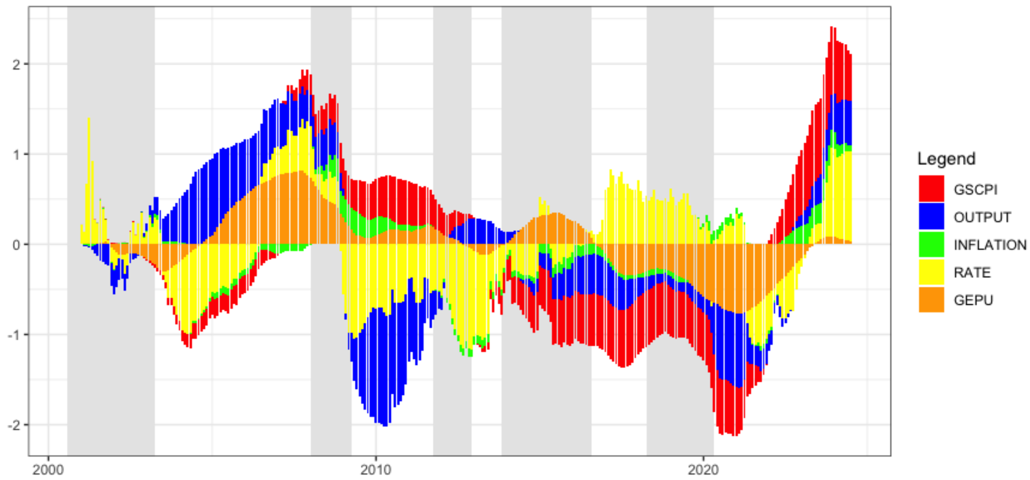
The GFC was a major global event that corresponds with a clear reduction in output growth. There was also a decrease in inflation during this period, likely reflecting the contraction in aggregate demand.

3.2.5. Post-GFC

In the aftermath of the GFC, output growth was primarily driven by demand shocks in the aftermath of the GFC period. During that time, supply chain pressures began to play a more noticeable role[7], where demand shocks were the dominant contributing factor, significantly lowered inflation during this period.

[7] The increase in inflation can be attributed to natural disasters (e.g., the Tohoku earthquake and Thailand flooding in 2011) (e.g., Benigno et al., 2022, Ascari et al., 2024).

Figure 7: Historical Decomposition of Rate



Shaded areas indicate OECD recession dates.

3.2.6. *COVID-19 Pandemic*

COVID-19 emerged as a pandemic in December 2019 and swiftly spread across the globe, leading to severe consequences such as widespread fatalities, economic stagnation and heightened uncertainty. The pandemic's effects were profound and persistent, prompting lockdowns and other measures to mitigate the spread of the virus.

The COVID-19 pandemic severely disrupted global supply chains, with factory closures, lockdowns, and mobility restrictions causing bottlenecks, surging shipping costs, and extended delivery times. Despite these disruptions, demand shocks remained a dominant force in output growth, with GSCPI shocks also playing a significant role during 2020. The pandemic notably impacted inflation, as global supply chain pressures substantially contributed to inflationary pressures (e.g., Benigno et al., 2022, Ascari et al., 2024).

3.2.7. *Recent Period (Post-Pandemic)*

As the effects of the pandemic began to subside, output growth started to stabilize. The role of global supply chain pressures has led to an inflationary environment to the extent that it was a dominant factor for this sample time period, albeit the effect of global supply chain disruptions has been diminishing. These disruptions contributed to amplifying inflation during the post-pandemic period. Additionally, surging energy and food prices due to the Russia-Ukraine conflict further exacerbated inflation.[8] The influence of demand shocks continues to be significant, but the overall inflation rate is stabilizing, though the persistence of inflationary pressures has had a notable impact on interest rates.

3.3. *Additional Models (Robustness)*

To enrich the robustness of the economic analysis, we include five alternative models:

[8] Zhang et al. (2023) find that the Russia- Ukraine conflict, which began in February 2022 and is ongoing at the time of this writing, led to an increase crude oil prices and volatility. Özocaklı et al. (2024) find that international grain prices (wheat, maize and barley) spiked during the onset of the ongoing Russia-Ukraine conflict. Ginn (2023*b*) shows that while energy and food inflation can create a "second round" effect on headline inflation, agriculture inflation has the most significant impact on aggregate inflation.

- **Model II**: the model is estimated prior to 2020 (i.e., before the start of the global pandemic). The IRFs are provided in Figure 10 in the Appendix.

- **Model III**: we replace output growth with the output gap. The IRFs are provided in Figure 11 in the Appendix.

- **Model IV**: we replace GDP based on PPP with nominal GDP, which is used in the time-varying calculation of the relative proportions to determine global economic variables. The IRFs are provided in Figure 12 in the Appendix.

- **Model V**: we estimate the Baseline Model using two lags (based on Schwartz information criterion). The IRFs are provided in Figure 13 in the Appendix.

- **Model VI**: we change the ordering in the Baseline Model such that Global EPU is ordered second (Baker et al., 2016).[9] The IRFs are provided in Figure 14 in the Appendix.

The empirical findings from the six models demonstrate that supply chain shocks are an important conduit on economic conditions.

4. Conclusion and Policy Implications

The COVID-19 pandemic exposed critical vulnerabilities in global supply chains, leading to widespread production delays and shortages. As economies recovered, surging demand quickly outpaced supply, highlighting the fragility of interconnected supply networks. This paper investigates the global economic consequences of these disruptions, focusing on their impact on business cycle synchronization and economic uncertainty.

We employ a Bayesian Vector Autoregression (BVAR) model using data from 22 economies to analyze the transmission of global supply chain shocks. Our results indicate that supply chain pressures amplify economic uncertainty, disrupt output, and contribute to inflationary pressures. These shocks propagate through global supply networks, intensifying the challenges for policymakers, who must account for the international nature of these disruptions when designing economic policies.

This study underscores the importance of understanding the global dimensions of supply chain shocks, particularly as economies become more integrated and vulnerable to cascading disruptions. Our findings provide novel insights into the role of supply chain pressures in shaping post-pandemic inflation dynamics and broader economic stability.

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[9] The rationale for maintaining that GSCPI is ordered first (i.e., is contemporaneously exogenous) follows the exogenous nature of GSCPI which can influence EPU. GSCPI is often driven by external factors (e.g., geopolitical tensions, pandemics, trade restrictions) which are largely exogenous, implying that GSCPI can be seen as an external shock thereby setting off a chain of reactions, which can subsequently increase EPU. This theoretical foundation supports the notion that supply chain disruptions are a primary source of shocks, while policy uncertainty is a reactionary variable.

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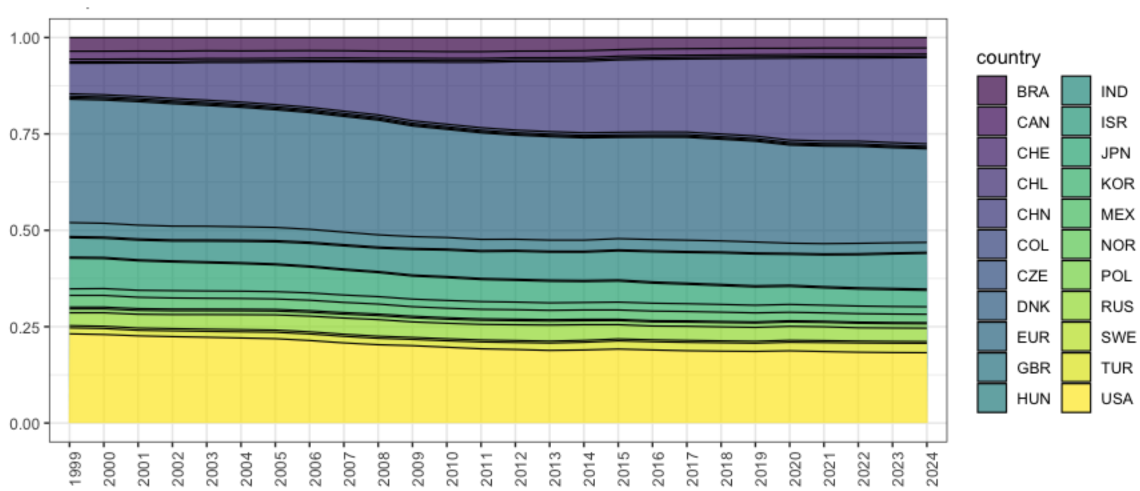
5. Appendix

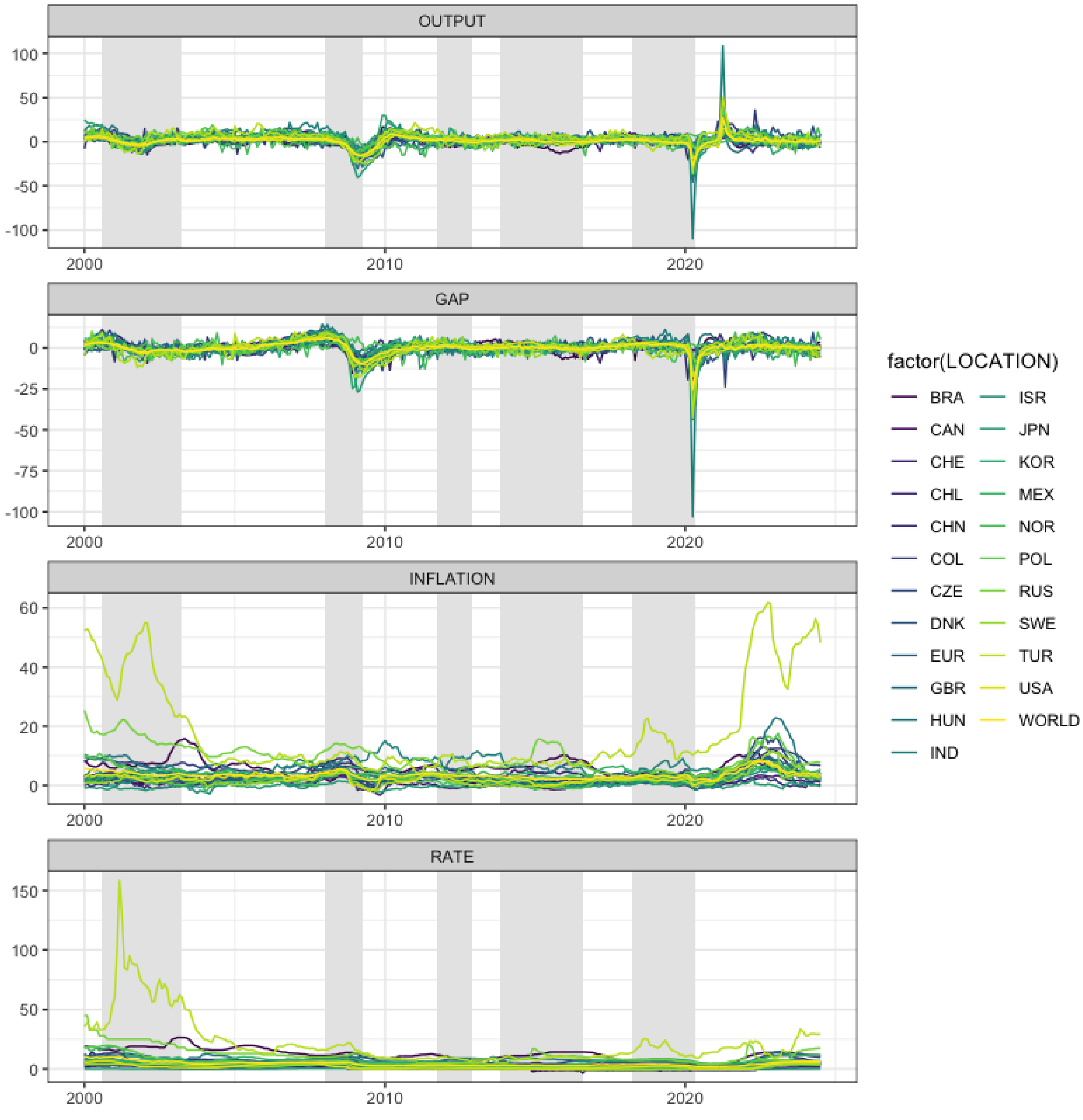
5.1. International Data

Figure 8: Time Varying GDP Weighted Index



Source: IMF data (in purchasing power parity terms).

Figure 9: International Economic Data



Shaded areas indicate OECD recession dates.

5.2. Alternative BVAR Models

Figure 10: BVAR IRFs (Model II)

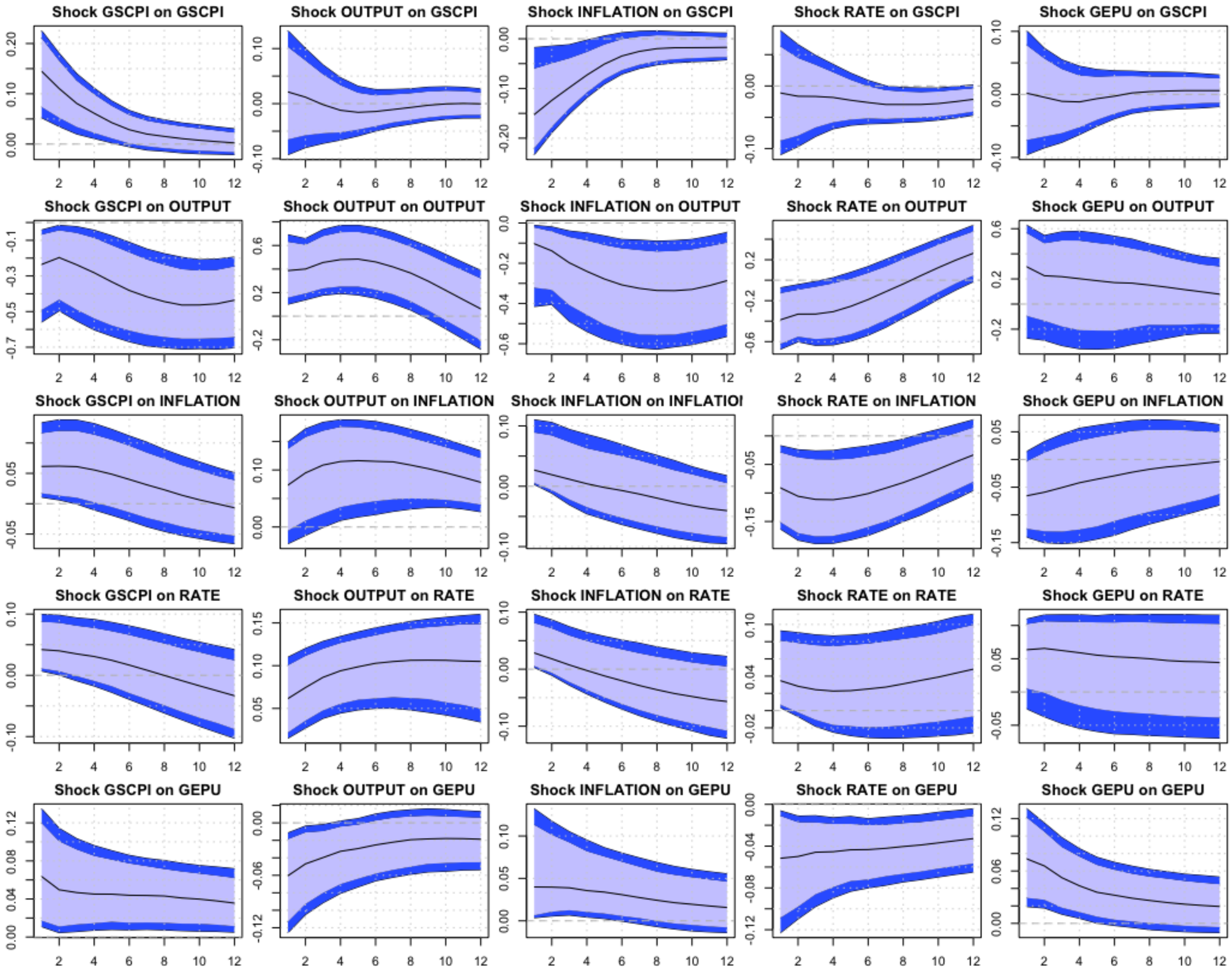


Figure 11: BVAR IRFs (Model III)

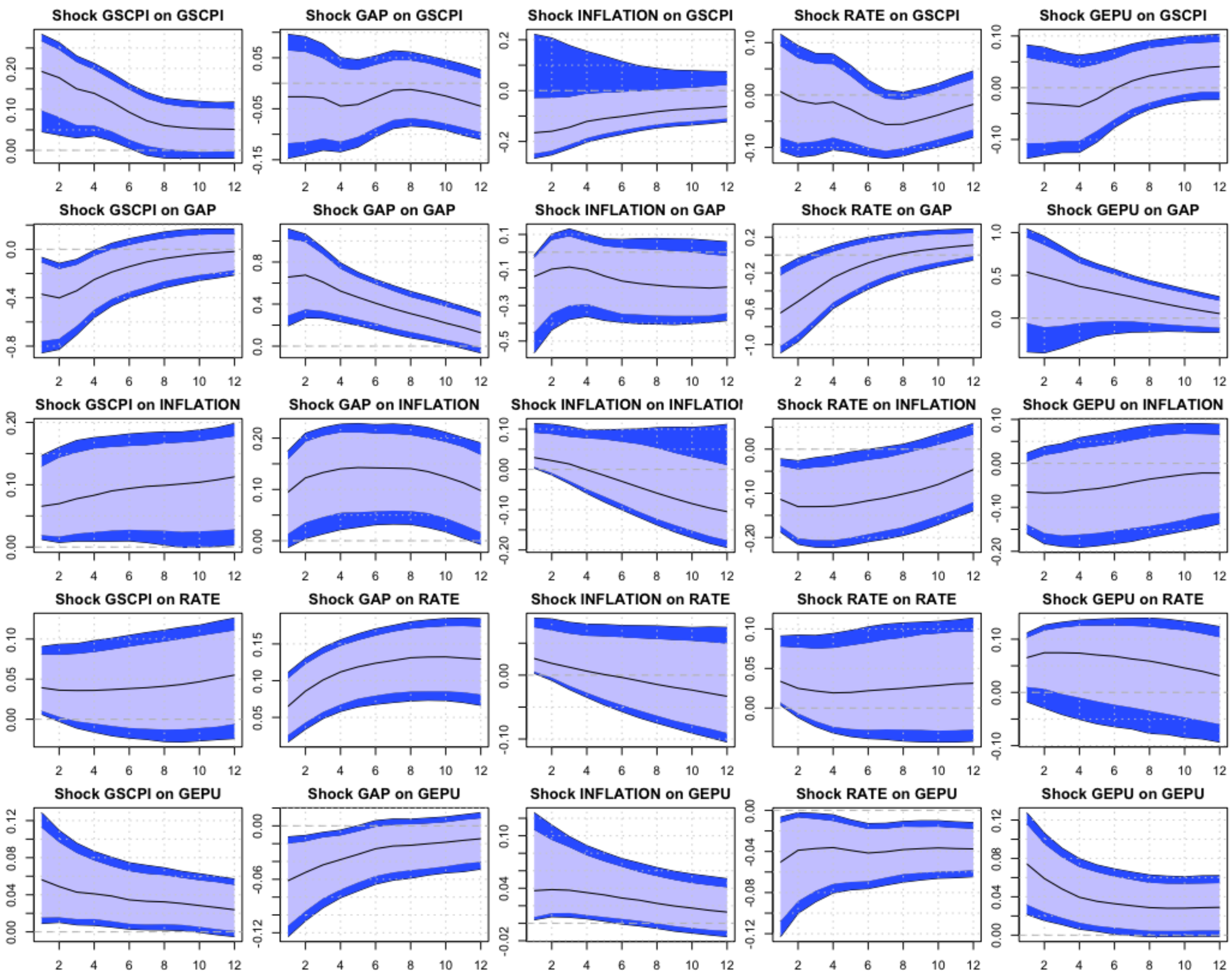


Figure 12: BVAR IRFs (Model IV)

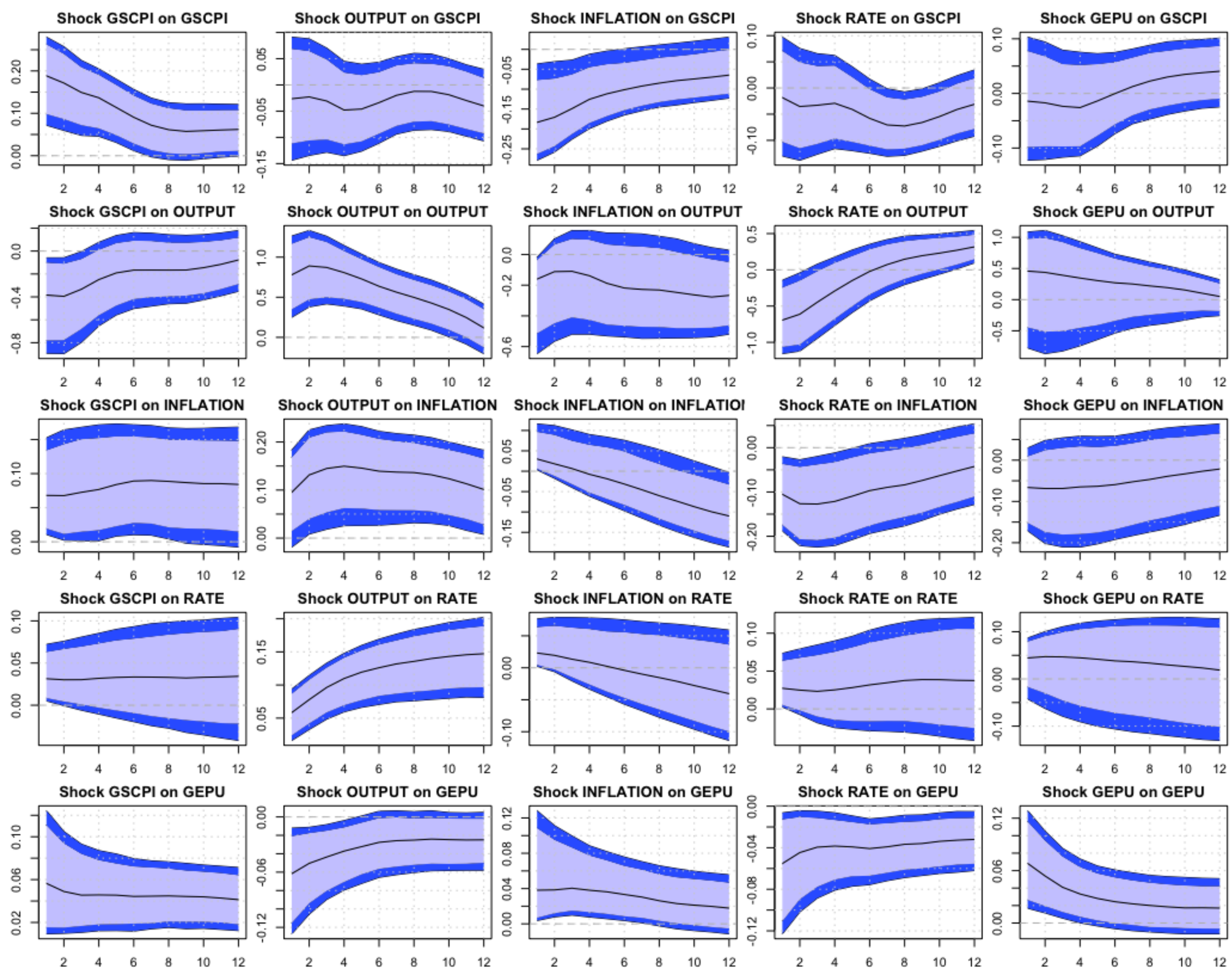


Figure 13: BVAR IRFs (Model V)

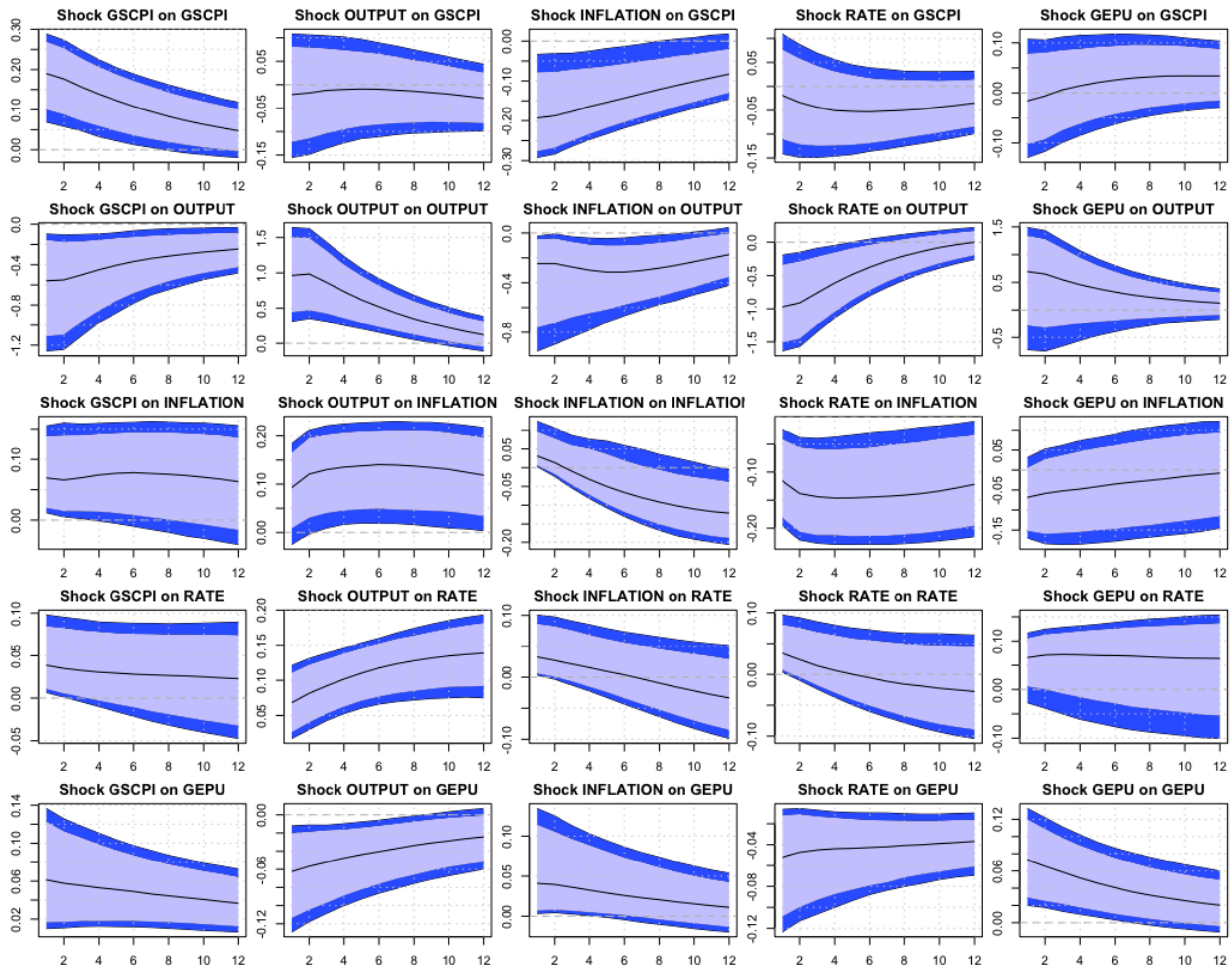


Figure 14: BVAR IRFs (Model VI)