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Supply Drivers of US Inflation Since the COVID-19 Pandemic

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Abstract

This paper examines the contribution of several supply factors to US headline inflation since the start of the COVID-19 pandemic. We identify six supply shocks using a structural VAR model: labor supply, labor productivity, global supply chain, oil price, price mark-up and wage mark-up shocks. Our shock identification relies mainly on sign restrictions. But for the global supply chain shock, we propose a new identification scheme combining sign, narrative and variance decomposition restrictions. Historical decomposition results suggest that global supply chain and oil price shocks are the biggest supply contributors to the US inflation during the pandemic. In contrast, labor shortages only mildly contribute to inflation, but their impact on output is larger in that period. Additionally, price and wage mark-up shocks start to significantly contribute to inflation only towards the middle of 2022. Finally, our analysis, which also allows the identification of monetary policy and aggregate demand shocks, suggests that demand and supply factors are almost equally responsible for the movements in the inflation rate during the pandemic.

Topics: Business fluctuations and cycles, Econometric and statistical methods, Inflation and prices

JEL codes: C32, E31, E32

Résumé

Cette étude examine la contribution de divers facteurs d'offre à l'inflation globale aux États-Unis depuis le début de la pandémie de COVID-19. Nous identifions six chocs d'offre à l'aide d'un modèle VAR structurel : chocs liés à l'offre de travail, à la productivité de la main d'œuvre, aux chaînes d'approvisionnement mondiales, aux cours du pétrole, aux majorations de prix et aux hausses salariales. Cette identification s'appuie principalement sur les restrictions de signe. Cependant, pour les chocs liés aux chaînes d'approvisionnement mondiales, nous proposons un nouveau schéma d'identification qui combine les approches de restrictions de signe, narrative et de décomposition de la variance. Les résultats de la décomposition historique donnent à penser que les chocs liés aux chaînes d'approvisionnement mondiales et aux cours du pétrole ont été les plus importants facteurs d'offre ayant contribué à l'inflation aux États-Unis durant la pandémie. Par contraste, les pénuries de main-d'œuvre n'ont que légèrement contribué à inflation, mais leur incidence sur la production a été plus grande durant la même période. En outre, ce n'est que vers le milieu de 2022 que les chocs liés aux majorations de prix et aux hausses salariales ont commencé à contribuer de façon significative à l'inflation. Enfin, notre analyse, qui permet aussi d'identifier les chocs de politique monétaire et de demande globale, montre que les facteurs d'offre et de demande ont contribué de manière presque égale aux variations du taux d'inflation durant la pandémie.

Sujets : Cycles et fluctuations économiques, Méthodes économétriques et statistiques, Inflation et prix

Codes JEL : C32, E31, E32

1 Introduction

At the beginning of the Covid-19 pandemic, the inflation rate fell sharply in the US. However, it quickly began to rise again in early 2021, reaching levels that are far higher than the Federal Reserve's target of 2%. As of June 2022, the inflation rate was 8.6% on a year-over-year basis. In addition to demand factors, many scholars have highlighted the significance of domestic and global supply factors to US inflation. Covid-19 lockdowns all around the world disrupted global supply chains and contributed to inflationary pressures by increasing the price of imported intermediate inputs as well as shipping costs (Benigno et al., 2022). Local lockdowns in the US exacerbated supply bottlenecks by decreasing labor supply and leading to a lower level of production (Barnichon and Shapiro, 2022; Di Giovanni et al., 2022). Higher level of consumer prices and tight labour markets since the opening of economies have prompted workers to demand greater pay, raising fears of further inflation as a result of the wage-price spiral (IMF, 2022). Oil prices have surged and production costs have risen as a result of the war in Ukraine and OPEC decisions. Some have argued that the widespread increase in prices has allowed firms to either charge higher markups over marginal costs or easily pass the increase in costs to their prices (Bräuning et al., 2022; Konczal and Lusiani, 2022). Lastly, the pandemic has affected labor productivity through several channels (Handwerker et al., 2020).[1] Changes in labor productivity, in turn, could have affected inflation through wages and supply of goods and services.

This paper aims to quantify the contribution of each of these supply factors to the US headline inflation. While we are aware that demand also plays a significant role, we contribute to the literature by providing a comprehensive approach to the supply-side forces driving inflation. In our empirical model, we analyze not only commonly used supply

[1]The impact of the pandemic on labor productivity is not conclusive. On the one hand, higher use of digital services and automation could have increased labor productivity (Luca et al., 2020; Leduc and Liu, 2020; Chernoff and Warman, 2022). In addition, compositional effects generally observed during recessions, such as the loss of low-productivity jobs and the exit of low-productivity firms, pushed up aggregate labor productivity especially during the early stages of the pandemic (Stewart et al., 2022). On the other hand, prolonged lockdowns might have lowered productivity due to lower morale and more parenting responsibilities (Berube and Bateman, 2020). In addition, lower labor mobility, lower global trade and investment in physical capital during the pandemic could have affected labor productivity negatively (Baldwin and Di Mauro, 2020).

shocks in the literature, but also supply chain issues, which is a relatively new aspect to consider in our understanding of inflation dynamics during the pandemic. Understanding which supply factors hit the economy is crucial for policymakers when tailoring policies and reforms that depend on the needs of the economy. In addition, while some of the aforementioned supply factors lower the potential capacity of the economy and shift the *long-run* aggregate supply, others – such as price and wage mark-up shocks – move only the *short-run* aggregate supply. When estimating potential output and determining the appropriate policy, monetary authorities must differentiate the supply elements along this dimension.

We identify six supply shocks hitting the US economy using a structural VAR model: labor supply, labor productivity, global supply chain, oil price, price mark-up and wage mark-up shocks. In addition, we identify two main demand shocks: aggregate demand and monetary policy. Our data cover several US macro variables, a world oil price, and a global supply chain pressure index proposed by Benigno et al. (2022). Our identification relies mainly on sign restrictions; however, we also utilize narratives and forecast error variance decomposition restrictions for the identification of global supply chain shocks. Our theory-driven sign restrictions mostly follow the textbook New Keynesian model with labor market participation (Galí, 2015; Galí et al., 2012). This model allows us to identify various supply shocks thanks to their differential effects on labor market variables. To orthogonalize oil price shocks with respect to the US economy, we follow commonly used sign restrictions similar to those in Baumeister and Hamilton (2019), Kilian and Zhou (2018), and Kilian and Murphy (2014).

Our results indicate significant contributions from supply factors, especially from supply chain and oil price shocks, to inflation over the pandemic period. In the first year of the pandemic, supply chain shocks and labour supply shocks – to some extent – drive inflation up while the lack of demand and insufficient expansionary monetary policy drives inflation down. Since the demand factors are predominant in 2020, inflation decreases overall. We observe that labor supply shocks due to lockdowns significantly contribute to negative output growth while their contribution to inflation is relatively mild. In the second year of the pandemic, supply factors stay alive while demand forces stop negatively affecting inflation and begin to increase it. Significant contributions from the oil shock causes an increase in the inflation rate above target levels. Lastly, in the third year of the pandemic, we observe additional oil and demand shocks both exacerbating inflation while other factors continue to drive inflation up. We find that the contribution of supply chain shocks slowly decreases while that of wage and price mark-up shocks somewhat increase towards the end of our sample, as of June 2022. Our results are robust to a series of specification and identification-related robustness tests.

We also contribute to the literature by proposing a new identification scheme for global supply chain shocks. Unlike the other shocks in our model, supply chain shocks cannot be identified only by sign restrictions. This is because, at present, the theory underlying supply chains and the effects of fundamental shocks on global supply chain indices is still not conclusive enough to impose a theory-driven sign identification scheme. To complement the sign restrictions, we employ other approaches such as narrative and forecast error variance decomposition (FEVD) restrictions. For the narrative approach, we follow Antolín-Díaz and Rubio-Ramírez (2018) and Ludvigson et al. (2021) and select key events that are commonly regarded as disruptions in global supply chains. For some major incidents, we also require magnitude restrictions. For the FEVD restrictions, which sharpen the identification, we follow Weale and Wieladek (2016) and Volpicella (2021). Our results suggest that narrative restrictions aid in separating supply chain shocks mostly from labor supply and oil price shocks, while FEVD restrictions help them to be distinguished from all other supply shocks almost uniformly. Overall, we recommend utilizing these extra restrictions to achieve identification for the supply chain shock.

Our paper is related to the literature that studies supply drivers of inflation during the pandemic. Benigno et al. (2022) propose an indicator measuring pressures that arise at the global supply chain level and show that it is closely related to inflation over the pandemic period. We use their proposed index, but we distinguish its impact on inflation from other various supply and demand shocks in a multivariate system. Di Giovanni et al. (2022) offer a model-based quantitative exercise and study the role of supply bottlenecks, which they define as sector-specific labor supply shocks. Note that their model omits other potential supply drivers of inflation such as mark-up shocks. They find that the contribution of supply bottlenecks to the increase in inflation is around 33%–37%. Similarly, we find a 39% contribution of supply bottlenecks, which include supply chain, oil price, labor supply and labor productivity shocks in our analysis. However, the total contribution of supply factors increase to 49% when price and wage mark-up shocks are also taken into account. Note that the type of supply shocks that mainly affect the productive capacity plays a considerably larger role than mark-up shocks. Thus, the shocks likely shift the long-run aggregate supply rather than the short-run aggregate supply. This suggests that potential output in the US has been considerably lower than pre-pandemic levels, which could have possibly impacted the level and especially persistence of inflation.

Our paper is also related to the literature that studies the split between demand and supply factors related to inflation during the pandemic. Shapiro (2022) divides the personal consumption expenditures basket into supply- and demand-driven groups by utilizing unexpected comovements in prices and quantities. His results suggest that supply factors explain about half of the rise in inflation during the pandemic, similar to our findings when we group all supply factors. Eickmeier and Hofmann (2022) identify these factors using a principal component analysis, whereas Ruch and Taskin (2022) benefit from corporate earnings to judge the imbalance between supply and demand. Although these papers quantify the contribution of supply factors relative to demand, they do not distinguish among various supply shocks.

On the demand side, some scholars attribute a considerable portion of the rise in inflation to monetary and fiscal policy mistakes. Reis (2022) and Summers (2022) emphasize the cost of a delayed monetary policy response to increases in inflation. Jordà et al. (2022), Jordà and Nechio (2022) and Summers (2021) underline the role of fiscal expansions in the sharp increase in inflation. Our results highlight that monetary policy significantly contributes to inflation, especially in 2021 during which authorities use the “transitory” language in their guidance. We also find the aggregate demand increasingly contributes to the rise in inflation following the month when the second fiscal stimulus is announced under the Biden administration in 2021. Overall, in our framework, demand factors including monetary policy shocks are found to contribute to half of the rise in US inflation.

The rest of the paper is organized as follows. Section 2 explains the sample data. Section 3 introduces the econometric model and discusses the shock identification. Section 4 presents the findings and discusses various robustness checks. Section 5 concludes. Additional figures are provided in the Appendix.

2 Data

Our dataset consists of 8 variables at a monthly frequency spanning the time period between January 1998 and June 2022. The variables that are US-specific include the logarithm of the real gross domestic product (GDP), logarithm of the consumer price index (CPI), the effective federal funds rate (FFR), the logarithm of the real wages (WAGE), the logarithm of the total hours (HOUR), and the labor force participation rate (PR). The remaining 2 variables are the logarithm of the West Texas Intermediate crude oil price (WTI) and the Global Supply Chain Pressure Index (GSCPI). We transform the nominal variables such as wages and oil prices into real by dividing them by the US CPI. For the FFR, during zero lower bound (ZLB) episodes, we use the shadow rate provided by Wu and Xia (2016). The monthly real GDP series is obtained from the Macroeconomic Advisers[2], the GSCPI is acquired from the Federal Reserve Bank of New York, and the other series can be obtained from the Haver Analytics or Federal Reserve Economic Data (FRED) database.

While most of these variables are well-known and widely used in the literature, the GSCPI is a newly constructed measure by Benigno et al. (2022). Let us now discuss its components further, which will be helpful when we discuss the identification of supply chain shocks. The GSCPI is an index capturing global supply chain conditions. Factors that put pressure on the global supply chain are (i) global transportation costs and (ii)

[2]Macroeconomic Advisers, which is part of S&P Global Market Intelligence, produces a monthly real GDP index that is an indicator of real aggregate output consistent with real GDP in the National Income and Product Accounts. The index can be downloaded from www.macroadvisers.com.

supply chain-specific issues such as port congestions and shortage of containers or truck drivers. The transportation costs cover the cost of shipping raw materials, containers, and air transportation that are captured by the Baltic Dry Index, Harpex Index, and air freight prices for the inbounds and outbounds between US-EU and US-Asia. The supply chain-related components rely on the Purchase Manager Index (PMI) surveys, with a special focus on the manufacturing sector in seven economies: China, the Euro Area, Japan, South Korea, Taiwan, the United Kingdom, and the United States. In particular, country-specific delivery times, backlogs, and purchased stocks sub-components of the PMI are used to capture supply chain delays, volume of incomplete orders, and inventory accumulation. Benigno et al. (2022) assert that demand side effects are eliminated from the index by orthogonalizing supply chain-related variables with respect to demand factors such as new orders and quantities purchased. Eventually, the GSCPI index is constructed by taking a principal component of 27 supply-side variables containing global transportation costs and country-specific supply chain measures.

3 Econometric Model and Shock Identification

We estimate the following reduced form VAR Model, for $t = 1, \ldots, T$,

$$\mathbf{Y}_t = \boldsymbol{\alpha} + \mathbf{A}_1 \mathbf{Y}_{t-1} + \cdot + \mathbf{A}_p \mathbf{Y}_{t-p} + \mathbf{u}_t,$$

where $\mathbf{Y}_t = (GDP_t,\ CPI_t,\ FFR_t,\ WAGE_t,\ HOUR_t,\ PR_t,\ WTI_t,\ GSCPI_t)'$ is the 8×1 vector of endogenous variables, $\mathbf{A}_j$s are the coefficient matrices for $j = 1, \ldots, p$, and $\mathbf{u}_t$ is the reduced-form errors. We estimate the model with Bayesian methods. In particular, we use the Normal-Wishart prior with some shrinkage, which is commonly used in the literature (see Giannone et al. (2015) for further discussion). This prior shrinks the diagonals of the first autoregressive coefficient matrix, $\mathbf{A}_1$, towards 1. This makes sense since we are using variables in log-levels, that is, nonstationary variables with possibly unit roots. On the other hand, the off-diagonals and coefficients in the other coefficient matrices, $\mathbf{A}_2, \ldots, \mathbf{A}_p$, are shrunk towards zero. The degrees of shrinkage are chosen optimally such that the marginal likelihood is maximized over a grid search on various shrinkage parameters. Our Bayesian sampling relies on 10,000 independent draws. For the lag length selection, the BIC and HQ criteria suggest $p = 2$, but portmanteau tests for serial correlations in residuals indicate that at least 3 lags are needed. Thus, we chose $p = 3$; however, our results are robust to different lag lengths, such as $p = 2, 6, 12$. Our results are also robust to using different priors, such as Normal-Diffuse or independent Normal-Wishart priors.

We assume that the structural economic shocks $\boldsymbol{\varepsilon}_t$ are related to the reduced-form errors $\mathbf{u}_t$ by $\mathbf{u}_t = \mathbf{B}\boldsymbol{\varepsilon}_t$, where $\mathbf{B}$ is called the contemporaneous impact matrix. To identify the structural shocks, we impose sign restrictions coupled with forecast error variance decomposition and narrative restrictions. We follow Arias et al. (2018) for the sign restriction algorithm, Weale and Wieladek (2016) and Volpicella (2021) for the variance decomposition restriction, and Antolín-Díaz and Rubio-Ramírez (2018) and Ludvigson et al. (2021) for the narrative restrictions.[3] The sign restrictions are derived from canonical medium-scale DSGE models – such as Galí et al. (2012) and Smets and Wouters (2007) – and strongly supported by the economic theory. However, for the global supply chain shock, theoretical models are scarce, they do not suggest particular response directions for many variables, and existing sign restrictions are not enough to identify it. Thus, we utilize variance decomposition restrictions as well as event-based narrative restrictions. Our empirical results suggest that we need these extra identifying restrictions to distinguish the global supply chain shock from other structural shocks.

3.1 Sign Restrictions

Table 1 summarizes the sign restrictions imposed on the contemporaneous impact matrix $\mathbf{B}$. We identify 2 demand shocks (aggregate demand and monetary policy) and 6 supply shocks (price mark-up, wage mark-up, productivity, labor supply, oil price, and supply chain). The last four supply shocks can be categorized as supply bottlenecks, which affect the productive capacity in the economy and are likely to change the flexible-price,

[3]For the econometric analysis, we utilize the Bayesian Estimation, Analysis and Regression (BEAR) toolbox (Dieppe et al., 2016); however, we heavily altered their code according to our identification strategy.

fundamental level of output. In contrast, the demand and mark-up supply shocks are more related to short-run fluctuations without affecting the fundamental level of output (Smets and Wouters, 2007).

Table 1: Sign restrictions

	Demand shocks		Supply shocks					
	Aggregate demand	Monetary policy	Price mark-up	Wage mark-up	Productivity	Labor supply	Oil price	Supply chain
Log real GDP	+	+	-	-	-	-	-	-
Log CPI	+	+	+	+	+	+	+	+
Federal funds rate	+	-						
Log real wages			-	+		+		
Log total hours			-	-	+	-		
Participation rate				+		-		
Log real oil price			-	-	-	-	+	
Global Supply Chain Pressure Index							+	+

Notes: This table shows the sign restrictions imposed on the impact matrix **B**. Empty cells indicate the coefficients that are not restricted.

The demand and supply shocks are separated from each other based on the responses of output and inflation: demand shocks drive output and inflation in the same direction while supply shocks pushes them in the opposite direction. In particular, an increase in the aggregate demand or an expansionary monetary policy shifts the demand curve up, resulting in an increase in the output and prices. On the other hand, supply side shocks shift the supply curve to the left, generating inflation while contracting the economy.

Let us focus on the supply shocks, except the supply chain shock. The identifications among them are mostly driven by responses of labor market variables. For instance, both price mark-up and productivity shocks drive output and inflation in different directions; however, price mark-up shocks lower total hours while productivity shocks increase them. This is because current output is demand driven; thus, GDP does not fall as much as potential output following a fall in productivity. Facing a fall in productivity, firms hire labor to meet demand. Also, the response of the hours separates the productivity shock from a negative labor supply shock. A wage mark-up shock pushes real wages up, which increases the labor market participation rate but forces firms to cut down on labor. These responses separate the wage mark-up shock from the price mark-up, productivity, and labor supply shocks. All of these domestic supply shocks have a negative effect on real oil prices, since they reduce production, which reduces demand for oil, and increases the general level of prices, which decreases oil prices in real terms. Lastly, the oil price shock is identified given that it increases real oil prices, unlike other supply shocks.

Except the supply chain shocks, all of the structural shocks are identified by the theory-driven sign restrictions. Even though we assume that supply chain shocks contract the output while being inflationary, and oil price shocks elevate the GSCPI since freight costs are one of the key determinants of this index, these are not enough to separate the supply chain shock from other supply shocks. We therefore employ supportive identification restrictions that are not directly imposed on the responses.

3.2 Variance Decomposition and Narrative Restrictions

One of these additional restrictions is imposed on the FEVD of the GSCPI. This corresponds to a quadratic inequality restriction on the columns of the matrix $\mathbf{B}$, which, in turn, reduce the width of impulse responses (Volpicella, 2021). Our particular assumption here is that the supply chain shock – compared to the other structural shocks – explains the largest fraction of the variation in the GSCPI upon impact and in the following two months. This assumption forces the supply chain shock to be more related to supply chain pressures, thus separating it from other supply shocks. From the US economy perspective, the variance decomposition assumption is reasonable since the GSCPI is a global variable and constructed by focusing on manufacturing firms across seven interconnected economies (countries from the Asia and Europe, and the US). Even though the US is one of them, it would be unreasonable if the US-specific shocks were the biggest determinants of the global supply chain pressures.

So far, we have imposed restrictions on the impulse-responses and FEVD. To further strengthen the separation of supply chain shocks, we use a narrative restriction approach (Antolín-Díaz and Rubio-Ramírez, 2018; Ludvigson et al., 2021) and impose event-based constraints on the time series of the structural shock itself.[4] We identify 8 historical events

[4]Recently, several studies use narrative restrictions in SVARs for shock identification (see, for instance, Budnik and Rünstler (2020), Larsen (2021), and Caggiano and Castelnuovo (2023) among many others.

consisting of natural disasters or accidents and recent lockdowns due to the COVID-19 pandemic. We believe that these events generated significant exogenous variations in the GSCPI and, thus, restrict the structural shocks accordingly. Some of these events clearly had a major impact on the US output or the real oil price, but our narrative restrictions are muted for the behavior of the structural shocks other than the supply chain shock. For instance, our narrative restrictions do not rule out another shock being the most important contributor to the variation in the GSCPI during these events. In this sense, narrative restrictions only may not be enough for a theoretical identification. But, together with the FEVD restrictions, they significantly reduce the admissible set of structural parameters and provide a strong empirical identification. Consequently, in our proposed identification scheme, a supply chain shock is accepted if it complies with the sign restrictions, explains most of the FEVD of the GSCPI, and agrees with the historical supply chain-related events.

Table 2: Narrative restrictions

Event	Date	Restriction on the supply chain shock
Hurricane Katrina	2005-Aug-23	> 1 std
Japan's earthquake and tsunami	2011-Mar-11	> 1 std
Hurricanes Harvey, Irma, and Maria	2017-Aug-17	positive
Wuhan lockdown	2020-Jan-23	> 2 std
Christmas lockdown	2020-Dec-15	positive
North American winter storm	2021-Feb-13	positive
Suez Canal obstruction	2021-Mar-23	positive
Shanghai lockdown	2022-Apr-05	positive

Notes: This table presents eight global supply chain-related events, their initial dates, and narrative restrictions imposed on the supply chain shock. For the restrictions, "positive" means that the supply chain shock is required to be positive and "> 1 std" and "> 2 std" mean that the magnitude of the supply chain shock is larger than its one and two standard deviations, respectively.

Table 2 lists 8 events together with their initial dates and narrative sign and magnitude restrictions imposed on the supply chain shock. Since there can be delays between the initial date of an event and its shock being materialized in the global supply chain, we take an agnostic approach and impose the restrictions to hold either upon impact or on the following month after the event. However, if an event occurred in the second half of the month, we extend the restriction horizon to a total of three months. For example, the

Wuhan lockdown starts on January 23, 2020; therefore, we rule out any potential structural parameter draws if they fail to generate a supply chain shock with a magnitude of at least 2 standard deviations in at least one of January, February, or March in 2020.

Next, let us discuss the rationale of choosing these 8 global supply chain events. Hurricane Katrina – the costliest and third-strongest hurricane ever to hit the US – created power outages, halted the Gulf shipping, and affected the worldwide commerce (Vigdor, 2008). The earthquake and a consequent tsunami that hit the Japanese city Tohoku in 2011 had a significant impact on the global supply chain (Inoue and Todo, 2019; Escaith et al., 2011), in particular within the automotive industry (Arto et al., 2015). Hurricanes Harvey, Irma, and Maria are among the costliest and strongest hurricanes in history. Having occurred back to back between late August and late September of 2017, they caused closures of significant ports, affecting not only the US and Caribbean regions but also supply chains globally (Palin et al., 2018).

Several studies show ramifications of pandemic lockdowns for the international trade, global production, and global supply chain (Bonadio et al., 2021; Meier and Pinto, 2020; Liu et al., 2021; Aiyar et al., 2022). Therefore, we include the regional lockdowns in Wuhan and Shanghai as well as the more widespread lockdown during Christmas and the New Year at the end of 2020 in the list of our supply chain events. Several studies exploit the time differential between the Wuhan lockdown and consequent ones to identify the isolated impact of the lockdown in Wuhan (Eppinger et al., 2020; Gerschel et al., 2020; Heise et al., 2020; Lafrogne-Joussier et al., 2022). They show that it generated significant disruptions in the production of firms around the world due to its damage to global supply chains and trade. On the other hand, by using congestion indices, Nie (2022) argues that the Shanghai lockdown was likely to generate smaller effects on the trade activity and global supply chain than the Wuhan lockdown.

Finally, the North American winter storm Uri (also known as Winter Storm Uri) and the Suez Canal obstruction put extra pressures on the already-fragile supply chain during the pandemic. The former affected parts of the US, Mexico, and Canada, generated one of the biggest power crises in the US, and created significant delays in freight and maritime transportation, resulting in an estimated economic loss of approximately $295 billion (Ritchie et al., 2022). The Suez Canal obstruction created a backlog of ships and prevented world trade valued around $54 billion (Lee and Wong, 2021).

4 Results

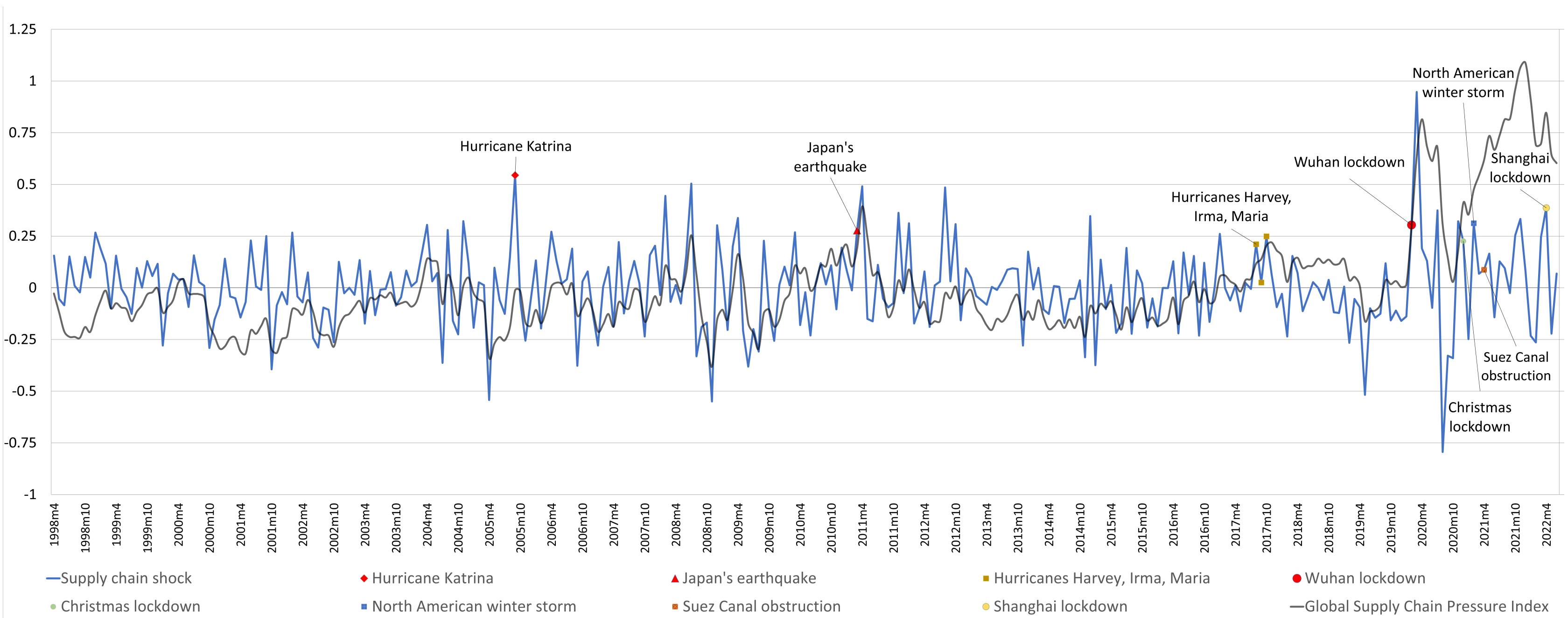
In this section, we discuss our empirical results. First, we present the time series of the estimated structural supply chain shock and investigate its identification strength under different identification schemes. Then, we evaluate the contribution of each shock to the US inflation and output over the pandemic by using historical decompositions.

4.1 Estimated Supply Chain Shocks

Figure 1 displays the median structural supply chain shocks (blue line, left axis) together with the GSCPI (black line, right axis) and narrative events. The standard deviation of the estimated shock is 0.25; thus, each horizontal line corresponds to one standard deviation of the shock. Note that the largest shock around an event does not necessarily occur in the same month as the event itself. For instance, Japan's earthquake occurred on March 11, 2011, yet the largest supply chain shock around this event is estimated to have occurred on April, 2011. The two largest supply chain shocks in our sample occurred during the Wuhan lockdown and Hurricane Katrina, corresponding to 3.8 and 2.2 standard deviation shocks, respectively. Subsequently, Japan's earthquake and Shanghai's lockdown are among the largest supply chain shocks, corresponding to 2.0 and 1.6 standard deviation shocks, respectively.

One might suspect that our estimated supply chain shock is *designed* to spike during these events, since they are part of the identification restrictions in the narratives. However, this is not the case. In an alternative identification scheme without any narrative restrictions, that is, when only the sign and FEVD restrictions are used, the aforementioned 4 supply chain events still correspond to significantly large supply chain shocks: 2.6, 2.0, 1.8, and 1.4 standard deviation shocks, respectively. These numbers are just slightly smaller

Figure 1: Supply chain shocks



Notes: This figure presents median supply chain shocks (blue line, left axis), the Global Supply Chain Pressure Index (GSCPI) (black line, right axis), and 8 global supply chain related events (various shapes and colors). The events are listed in Table 2 together with their dates and associated restrictions. The supply chain shocks are obtained from our baseline identification scheme that relies on sign, narrative, and FEVD restrictions. The standard deviations of the estimated shock and the GSCPI is 0.25 and 1, respectively. Thus, each horizontal line corresponds to one standard deviation.

than our baseline case. We also obtain similar comparison for the rest of the narrative events. This means that even without the narrative restrictions, significant supply chain shocks are estimated to occur around our selected events. However, what the narrative approach achieves is the elimination of implausible shocks during the event windows.

Next, we investigate the impact of different identification schemes for the supply chain shock. First, we focus on the percentage of contribution of each shock on the average forecast error variance of the GSCPI, presented in the top panel of Table 3. Let us start with the simplest identification scheme, called Scheme I, where we use only the sign restrictions and impose neither narrative nor FEVD restrictions. In this scheme, the forecast error variance of the GSCPI is explained almost equally by each shock, i.e., there is no particular shock that drives the GSCPI. This is likely an indication for an *unidentified* supply chain shock. In Scheme II, the identification restrictions include sign and narrative restrictions. By adding only the narrative restrictions, the contribution of the supply chain shock to the

Table 3: Forecast error variance decompositions

	Demand shocks		Supply shocks					
	Aggregate demand	Monetary policy	Price mark-up	Wage mark-up	Productivity	Labor supply	Oil price	Supply chain
Scheme I: sign	12.0%	10.8%	16.5%	12.5%	12.1%	13.9%	10.4%	11.9%
Scheme II: sign, narrative	10.8%	9.1%	16.1%	9.8%	10.2%	10.8%	7.4%	25.7%
Scheme III: sign, FEVD	10.4%	8.2%	12.3%	8.1%	8.3%	9.0%	6.9%	36.7%
Baseline: sign, narrative, FEVD	9.4%	7.8%	12.8%	7.3%	7.7%	7.9%	5.9%	41.1%

(a) Average FEVD of GSCPI

	GDP	CPI	FFR	WAGE	HOUR	PR	WTI	GSCPI
Scheme I: sign	10.5%	14.7%	13.0%	11.2%	10.1%	11.8%	15.2%	11.9%
Scheme II: sign, narrative	13.4%	12.3%	8.6%	9.4%	8.6%	10.3%	6.7%	25.7%
Scheme III: sign, FEVD	8.4%	16.1%	10.2%	7.3%	9.2%	9.8%	9.8%	36.7%
Baseline: sign, narrative, FEVD	10.2%	13.8%	8.0%	7.3%	8.5%	9.4%	6.4%	41.1%

(b) Average contribution of supply chain shocks to FEVDs of each variable

Notes: Top panel shows the average forecast error variance decompositions (FEVD) of the Global Supply Chain Pressure Index (GSCPI) under four different identification schemes (the baseline and three alternative schemes). The percentages indicate the contribution of each shock under each identification scheme. The bottom panel shows the average percentage contribution of the supply chain shock to FEVDs of each variable. The averages are taken over 24 months. Restrictions involved in each identification scheme are given next to the scheme names: the baseline identification contains sign, narrative, and FEVD restrictions; Scheme I contains only the sign restrictions; Scheme II contains both the sign and narrative restrictions; Scheme III contains both the sign and FEVD restrictions.

FEVD of the GSCPI increases from 11.9% to 25.7%. The increase in the explanatory power of the supply chain shock is taken mostly from other supply shocks, but especially from labor supply and oil price shocks. In Scheme III, the identification restrictions include sign and FEVD restrictions. The FEVD restrictions increase the contribution of supply chain shocks from 11.9% to 36.7%. This increase is taken almost uniformly from all other supply shocks. Finally, in our baseline identification, which entails sign, narrative, and FEVD restrictions, around 41% of the GSCPI is explained by the supply chain shock, around 42% of the GSCPI by the other five supply shocks (price mark-up shocks having the largest share), and around 17% of it by demand shocks.

Then, we examine the explanatory power of supply chain shocks for average FEVDs of each variable under different identification schemes, presented in the bottom panel of Table 3. When there are only sign restrictions (Scheme I), supply chain shocks explain average FEVDs of each variable roughly equally – with oil prices being explained the most. Including narrative restrictions (Scheme II) increases the explanatory power of supply chain shocks for the GSCPI significantly, while decreasing that for most of the variables, especially the price of oil. In Scheme III, where both sign and FEVD restrictions are imposed, the explanatory power of supply chain shocks for the GSCPI is even larger. Finally, in our baseline identification, which entails sign, narrative, and FEVD restrictions, supply chain shocks explain around 41% of the average FEVD of the GSCPI and 6% to 14% of the average FEVD of other variables.

Overall, these different identification schemes suggest that using only the sign restrictions might not be enough to identify supply chain shocks. Therefore, we recommend adding further restrictions, such as narrative or FEVD restrictions, to identify the supply chain shock. Narrative restrictions concerning lockdowns and natural disasters help separate supply chain shocks, mainly from labor supply and oil price shocks. In contrast, FEVD restrictions help them to be distinguished from all other supply shocks almost uniformly.

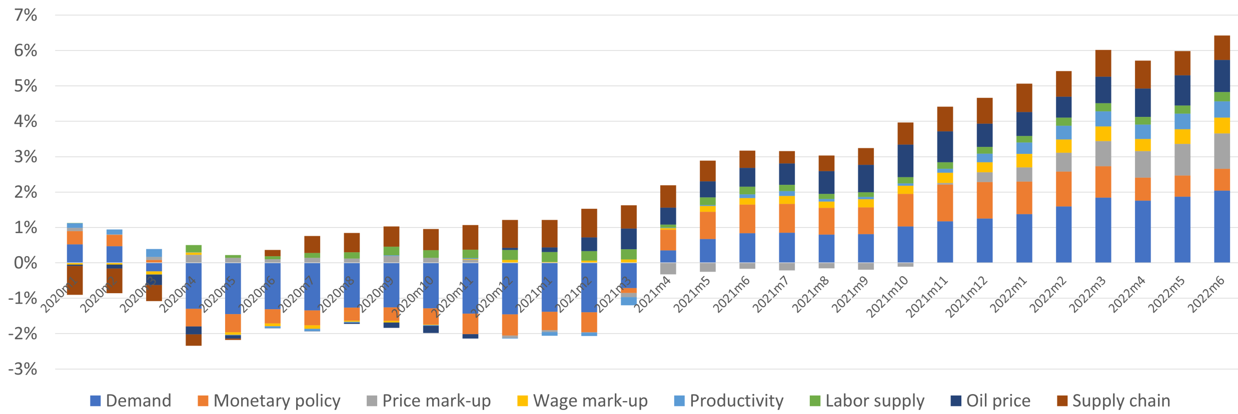
4.2 Historical Decompositions for Inflation and Output

Figure 2 shows the historical decomposition of the year-over-year US inflation rate since the beginning of 2020. At the beginning of the pandemic, we observe a sharp decline in aggregate demand that is consistent with the delay in spending, especially on services and durable goods that is highlighted in other studies (Chetty et al., 2020; Surico et al., 2020). The fall in demand reflects strict measures on social distancing implemented during this period. Monetary policy also contributes negatively to inflation, potentially reflecting the ZLB constraints. Thus, unconventional policies conducted at the beginning of the pandemic might not be stimulative enough at the beginning of the pandemic in generating financial conditions that the model predicts in the face of other structural shocks. However, these negative contributions are relatively mild, reflecting minor concerns on the ZLB constraint.

Supply constraints such as the fall in labor force and global supply chain problems start to affect inflation significantly only a few months after the pandemic starts. Also, their contribution gradually increases over time. Thus, the impact of such constraints come with a lag on inflation even though they drag output instantly as depicted in Figure 3.[5] This result is not surprising given that firms can initially weather supply constraints thanks to their stock of inventories.

[5]Estimated impulse-response functions (IRFs) show that a positive shock to global supply pressures gradually increases inflation reaching to a peak in eight months, while it drags output to a trough at the second month (see Figure A.1 in the appendix).

Figure 2: Historical decomposition of inflation (year-over-year)



Notes: The figure presents the contribution of each structural shock to the deviation of inflation rate from its steady state, that is, the rate implied by the model with initial conditions and no shocks. The steady-state year-over-year inflation is found to be around 2.3% and stable over time.

In the second year of the pandemic, supply shocks stay alive with additional oil price shocks, adding upward pressures on inflation. Furthermore, negative demand factors start to dissipate and eventually become positive, putting even more pressure on the inflation rate. Monetary policy is now no longer constrained and becomes more expansionary than the fundamentals suggest. Around this time, the "transitory" language was adopted just after inflation starts to increase, which might have contributed to it further. Similar to monetary policy shocks, aggregate demand shocks also push inflation up. Note that the turning point of demand shocks coincides with the fiscal stimulus package announced in March 2021 under President Biden. Overall, these results suggest that both supply and demand factors contribute to the initial rise of inflation in 2021.

Openings of economies in the third year of the pandemic increases inflation even further. The results point out persistent effects of supply chain constraints on inflation, although their impact starts to slightly diminish towards the end of our sample. In contrast, other supply shocks become increasingly more important in driving inflation. The contribution of oil price shocks becomes larger following the Ukraine war (March 2022). Moreover, price mark-up shocks increasingly contribute to the rise of inflation in recent months. This result could reflect the higher margins that firms charge during a widespread increase in prices. Thus, when practically all prices are rising, firms may notice a lower demand elasticity of pricing and far more easily pass those cost constraints onto their prices. The increase in the contribution of price mark-up shocks could also reflect residual factors in the inflation that we do not include in in our system, such as the increase in food inflation following the Ukraine war.

Tight labor markets still contribute to inflation via lower labor supply and higher wage mark-ups, albeit their contributions are small relative to other supply shocks. In addition, the fall in labor productivity exacerbates supply problems and starts to increase inflation significantly. The fall in productivity might reflect structural changes in the economy just after the opening of the economy. For instance, during the pandemic, many workers shifted from one industry to another, which potentially generated skill mismatches in the labor market during the opening. Throughout this transition, it is not surprising to observe a fall in labor productivity as workers are trained in their new jobs.

In addition to supply factors, opening up the economy completely in 2022 leads to substantially larger contributions from aggregate demand shocks. This is consistent with the fact that consumers, with more money in their pockets, may have begun making purchases they had put off in previous years. In contrast, monetary policy becomes considerably less of an inflationary force, reflecting the start of a tightening cycle in March 2022.

Overall, our results confirm the significance of supply factors in driving inflation up. Table 4 groups our structural shocks into demand and supply categories. Furthermore, for supply factors, it groups them into supply bottlenecks and mark-up shocks. Supply bottlenecks are defined as those shocks that affect the productive capacity of the economy, and thus the fundamental, long-run aggregate supply or the production function. They include labor supply, labor productivity, supply chain, and oil price shocks. Table 4 shows that the type of supply shocks that hit the US economy during the pandemic are mostly the supply bottlenecks rather than mark-up shocks. As a result, the potential output is lower, generating an excess demand in the economy even without any demand shocks. Since these shocks affect the potential output, they might have contributed to a more persistent inflation. This is in contrast to mark-up shocks, which generally affect short-run aggregate supply and can be considered temporary.[6]

Table 4: Relative contributions to inflation

Year	Demand shocks	Supply bottlenecks	Mark-up shocks
2020	58.5%	34.4%	7.1%
2021	47.1%	43.3%	9.5%
2022	43.9%	37.1%	19.0%
Pandemic average	51.0%	38.5%	10.5%

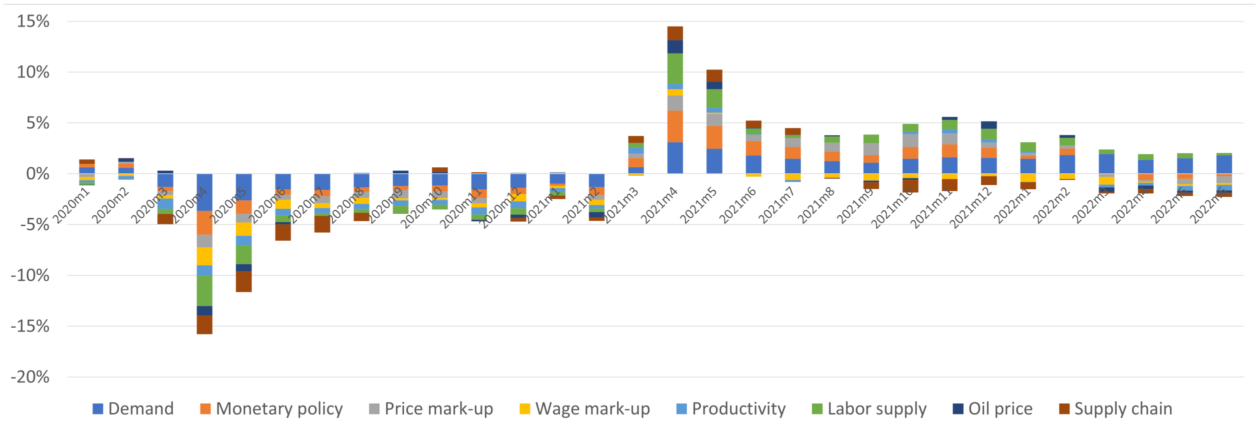
Notes: This table shows average relative contributions of shocks to inflation in 2020, 2021, 2022 (until June), and throughout the pandemic. The shocks are grouped into three categories: demand shocks is the summation of the aggregate demand and monetary policy shocks; supply bottlenecks is the summation of the productivity, labor supply, oil, and global supply chain shocks; mark-up shocks is the summation of the price and wage mark-up shocks.

Table 4 also shows that supply factors including markup shocks explain, on average, half of the fluctuations in inflation over the pandemic, while demand factors explain the other half. The contribution of supply factors steadily increases over years, first due to the supply bottlenecks in 2021 and then markup shocks in 2022. About 56% of the increase in inflation in the first half of 2022 can be attributed to supply shocks. Specifically, our results suggest that inflation still would have been high at around 6% instead of 8.6% in June 2022 had demand factors been neutralized, perhaps as a result of earlier tightening of monetary and fiscal policies.

Turning to output, Figure 3 illustrates the historical decomposition of year-over-year output growth rate. The picture is generally consistent with the dynamics explained for inflation above. Early in the pandemic, both negative supply and demand factors drive the output growth down. Normalization of these factors, especially on the demand side from extreme lows, leads to a quick pick up in output in 2021. Finally, persistent negative supply shocks in 2022 drive output down while demand factors drive it up. As a result, on net, output grows similarly to its historical trends.

[6] Our baseline IRFs also confirm that supply bottlenecks, on average, tend to have more persistent effects on inflation compared to price or wage mark-up shocks. See Figure A.1 in the appendix.

Figure 3: Historical decomposition of output growth (year-over-year)



Notes: The figure presents the contributions of structural shocks to the deviation of growth rate of output from its steady-state, thus, the rate implied by the model with initial conditions and no shocks. The steady-state year-over-year growth rate is found to be around 1.9% and stable over time.

It is worth noting two striking observations of output decomposition relative to inflation. First, in 2021, supply shocks positively contribute to the output growth rate, driving it higher than the trend growth rate, while they do not drive inflation down. In fact, supply constraints drive the inflation rate up in 2021. This is mainly because supply shocks, such as supply chain or labor supply shocks, have different persistence properties on the *level* of output and inflation. While these shocks immediately lower output, they have much more gradual impact on prices (see Figure A.1). Therefore, somewhat easing supply constraints in 2021 from very low 2020 levels might have instantly increased the growth rate of output but might not have had such an instant impact on inflation.

Second, shocks to labor force participation seem to be significant for the output growth while they are not very significant for inflation. As one of the factors of production, it is natural that these shocks significantly affect domestic production. But our results reveal that, empirically, firms do not significantly re-price their products because of this effect. This is partly because we do not observe significant and persistent increases in wages following these shocks. This finding is important and forces us to re-think the standard New Keynesian theory that quantitatively emphasizes the role of labor market tightness on output gap and inflation through wage and price Phillips curves (Galí, 2015).

4.3 Robustness

Lastly, we show that our results are robust to various alternatives both in terms of identification and modeling. Regarding identification, we perform 6 robustness checks where we relax, one by one, (1) both the narrative and FEVD restrictions, (2) the narrative restrictions, (3) the FEVD restrictions, (4) the magnitude restrictions in the narratives (i.e., we impose only positivity), (5) the FEVD restriction in the second month after a supply chain shock, and (6) the FEVD restrictions both in the first and second months after a supply chain shock. Regarding modeling, we perform two groups of robustness checks: (7) we use different lag length, $p = 2, 6, 12$, for the VAR model and (8) we use different priors such as Normal-Diffuse or independent Normal-Wishart priors for the Bayesian estimation.[7]

Our results are highly robust to the robustness checks (2)–(8). For instance, the correlation coefficient between the median structural supply chain shocks obtained from the baseline and each of these robustness cases is at least 0.95. Each robustness case results in only small changes that do not affect our baseline results.

The biggest deviation from our baseline results occurs in the robustness check (1). The main reason is that utilizing only the sign restrictions is unlikely to fully identify the structural supply chain shock. In this robustness check, IRFs have much wider confidence bands and the relative contribution of the supply chain shock during the pandemic (especially in 2020) diminishes to levels that are not in line with anecdotal evidence – its contribution appears to be attributed mostly to other supply bottleneck shocks. Hence, even though the main message of the paper stays roughly in line with the baseline, we recommend strengthening the identification provided by the sign restrictions only.

5 Conclusion

Various factors have been blamed for the rise in the US inflation since early 2021. The goal of this study is to investigate the supply side of this phenomenon. We particularly focus on global supply chain, labor supply, labor productivity, oil price, price mark-up and

[7] Robustness results regarding identification restrictions are given in the online appendix. Results related to all other robustness checks are available upon request.

wage mark-up shocks. We compute how much each of these supply shocks contribute to overall inflation in the US, with a special focus on the pandemic period. Since the demand side also plays a significant role in that episode, we include the aggregate demand and monetary policy shocks in our analysis.

We identify the shocks in a structural VAR model by using sign, narrative, and forecast error variance decomposition restrictions. One of the contributions of this paper is methodological; we propose an identification scheme for global supply chain shocks. Unlike other shocks in our model, sign restrictions are not enough to identify supply chain shocks since the economic theory, at present, does not provide conclusive relationships between global supply chains and economic fundamentals. Therefore, we utilize variance decomposition restrictions and key supply chain-related events, such as lockdowns and natural disasters, to pin down the global supply chain shocks.

We use historical decompositions to quantify the contribution of each shock to inflation. Our results point to important contributions, mainly from supply chain and oil price shocks, to inflation during the pandemic. The fall in labor force also contributes to the rise of inflation. However, its contribution to inflation is relatively mild even though it significantly contributes to output growth. In addition to these supply bottlenecks, mark-up shocks start to contribute to inflation towards the middle of 2022. Overall, supply factors explain half of the rise in inflation during the pandemic. The rest is attributed to demand factors.

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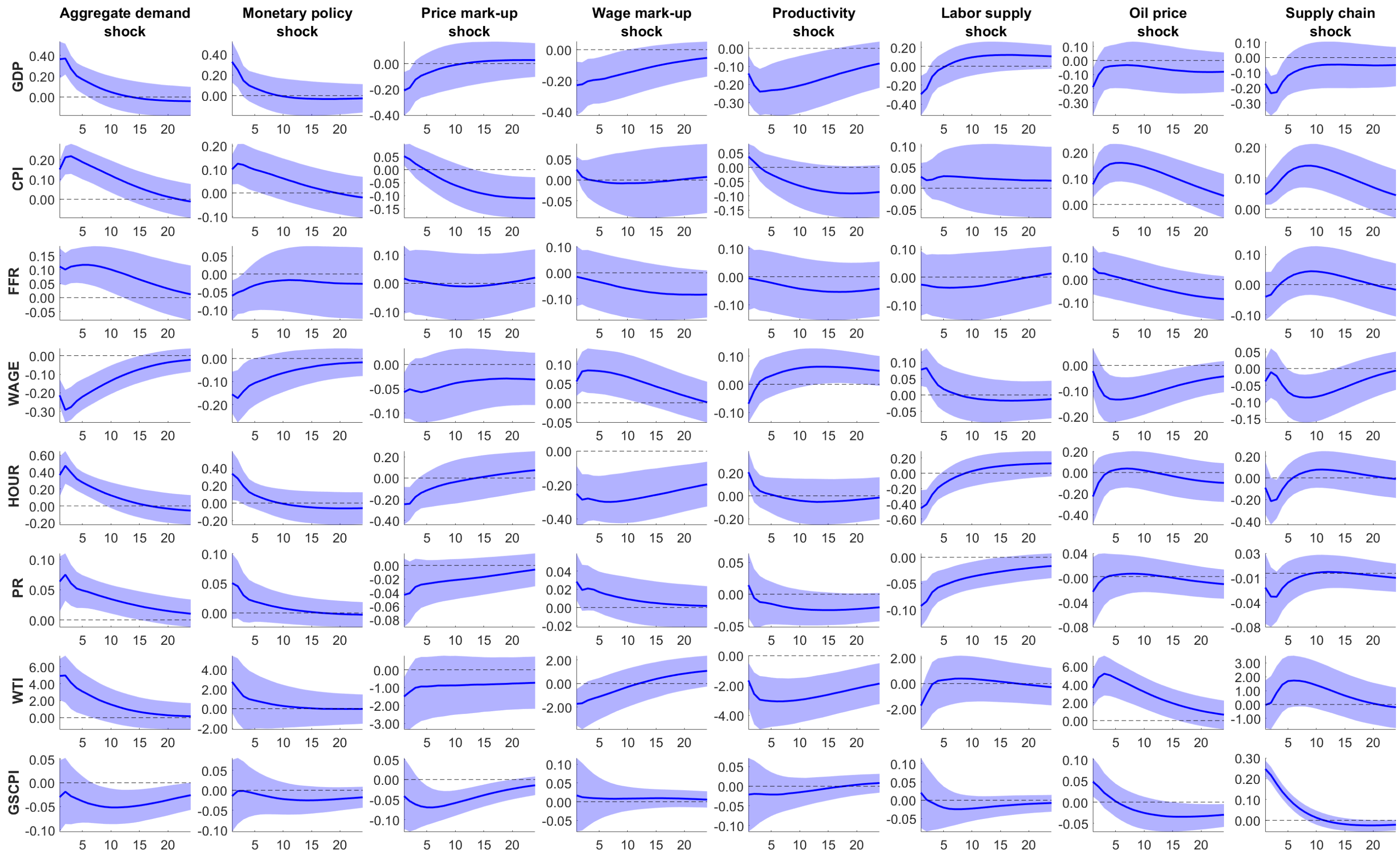
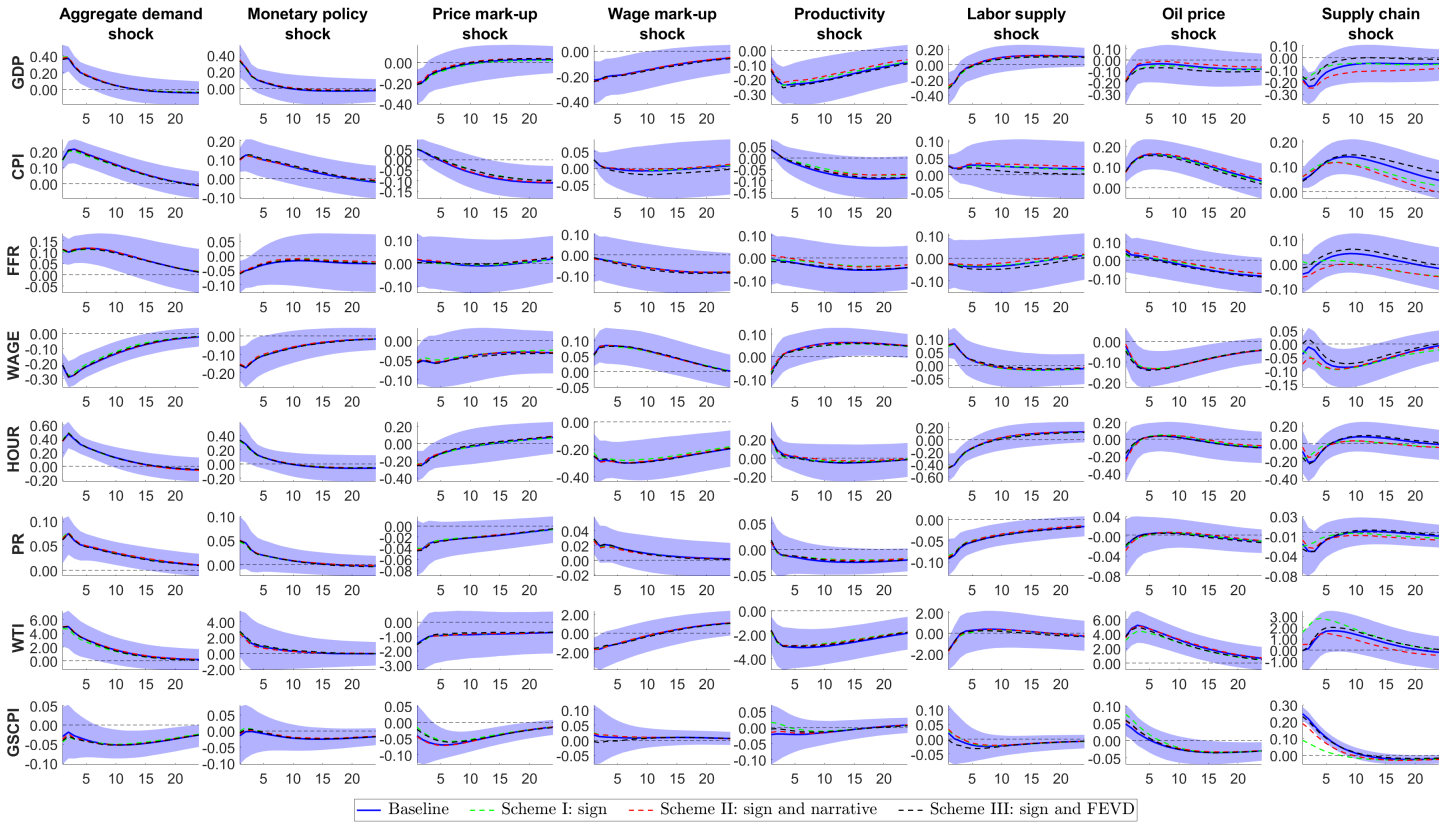
A Appendix

Figure A.1: Baseline IRF results



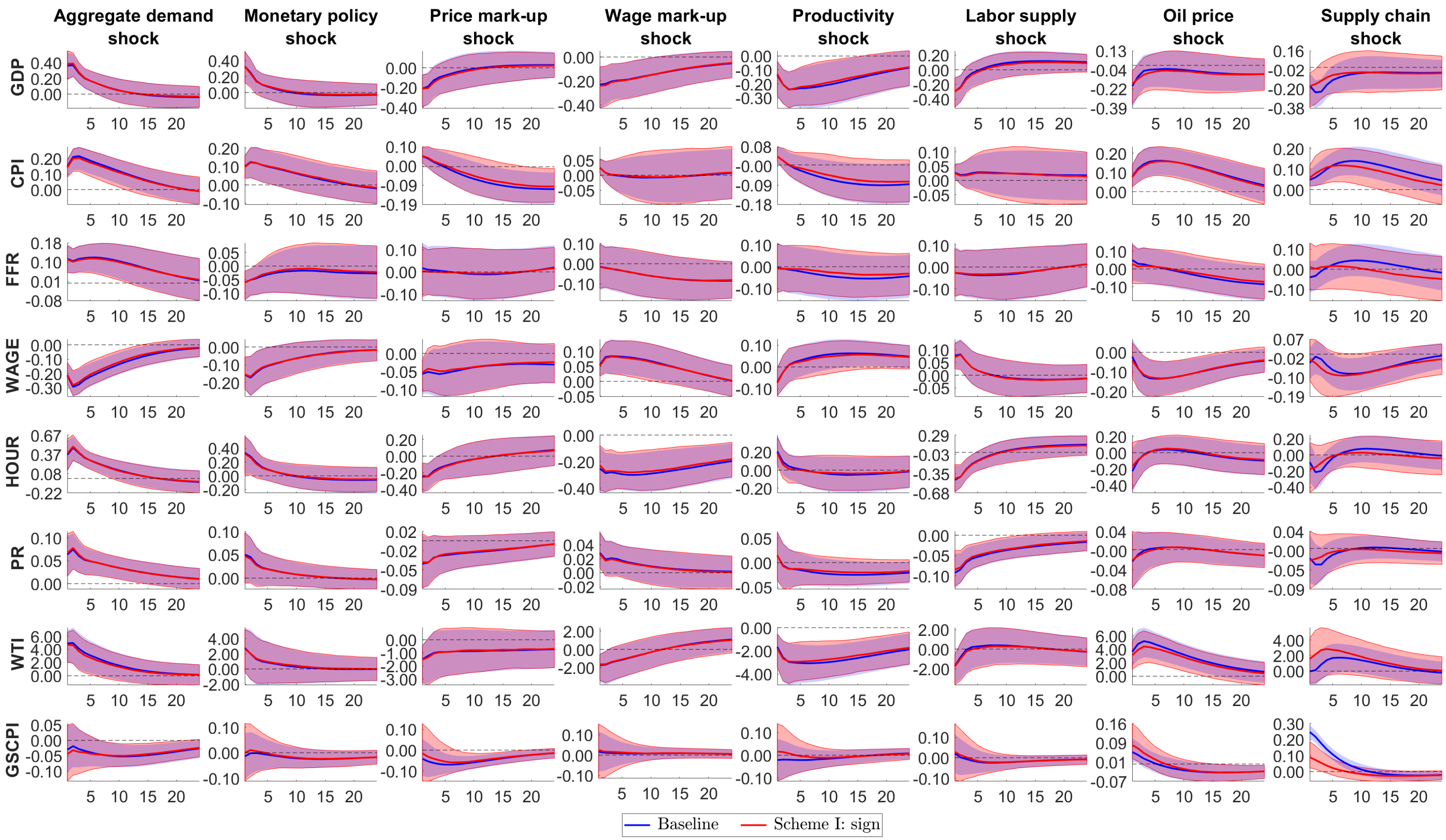
Notes: This figure plots responses to 1 standard deviation shocks, where variables are in the rows and shocks are in the columns. The responses are traced over 24 months. Solid blue lines represent median responses and shaded blue regions correspond to 68% confidence bands. GDP is the logarithm of the real gross domestic product; CPI is the logarithm of the consumer price index; FFR is of the effective federal funds rate; WAGE is the logarithm of the real wages; HOUR is the logarithm of the total hours; PR is the labor force participation rate; WTI is the logarithm of the West Texas Intermediate crude oil price; GSCPI is the Global Supply Chain Pressure Index.

Figure A.2: IRF comparison: Baseline vs three alternative identification schemes



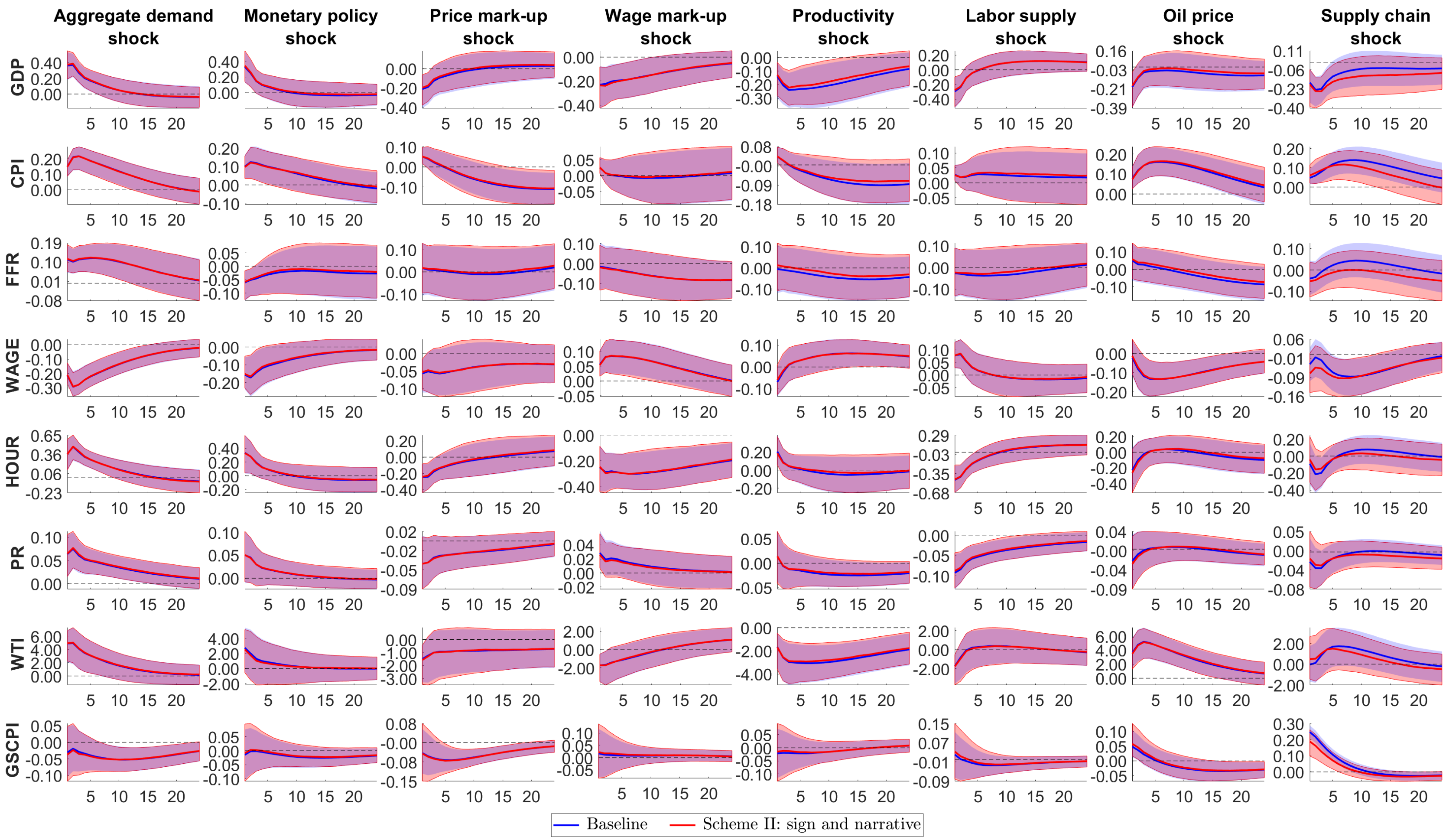
Notes: This figure plots responses to 1 standard deviation shocks in four different identification schemes. Variables are in the rows and shocks are in the columns. The responses are traced over 24 months. The baseline identification scheme, where sign, narrative, and FEVD restrictions are employed, is in blue where solid lines represent median responses and shaded regions correspond to 68% confidence bands. Scheme I utilizes only sign restrictions and its median responses are given in dashed green lines. Scheme II utilizes sign and narrative restrictions and its median responses are given in dashed red lines. Scheme III utilizes sign and FEVD restrictions and its median responses are given in dashed black lines. GDP is the logarithm of the real gross domestic product; CPI is the logarithm of the consumer price index; FFR is the effective federal funds rate; WAGE is the logarithm of the real wages; HOUR is the logarithm of the total hours; PR is the labor force participation rate; WTI is the logarithm of the West Texas Intermediate crude oil price; GSCPI is the Global Supply Chain Pressure Index.

Figure A.3: IRF comparison with alternative shock identifications: Baseline vs Scheme I: sign



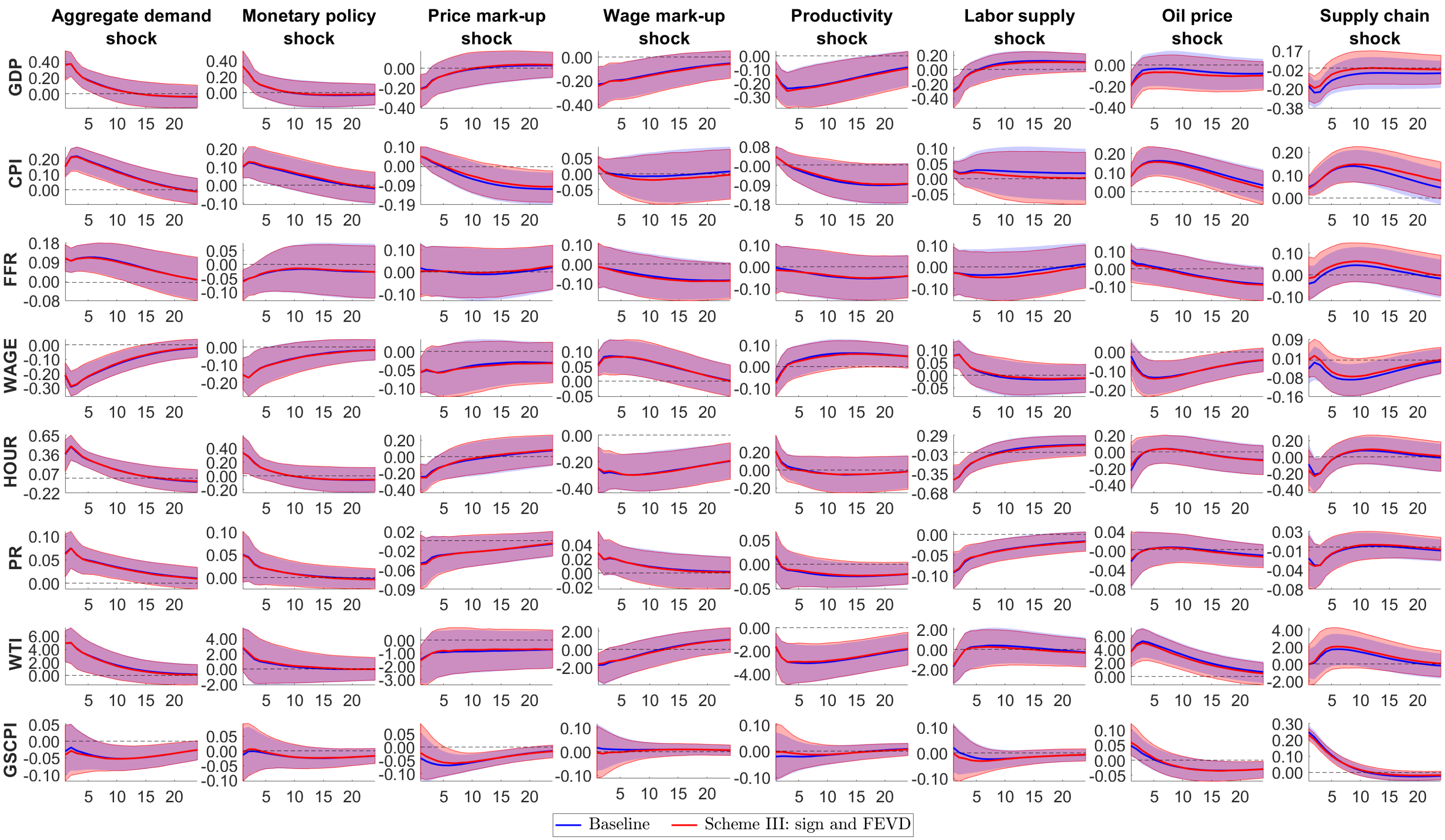
Notes: This figure plots responses to 1 standard deviation shocks in two different identification schemes: Baseline and Scheme I. The baseline identification scheme, where sign, narrative, and FEVD restrictions are employed, is in blue and Scheme I, where only sign restrictions are utilized, is in red. Solid lines represent median responses and shaded regions correspond to 68% confidence bands. Variables are in the rows and shocks are in the columns. The responses are traced over 24 months. GDP is the logarithm of the real gross domestic product; CPI is the logarithm of the consumer price index; FFR is the effective federal funds rate; WAGE is the logarithm of the real wages; HOUR is the logarithm of the total hours; PR is the labor force participation rate; WTI is the logarithm of the West Texas Intermediate crude oil price; GSCPI is the Global Supply Chain Pressure Index.

Figure A.4: IRF comparison with alternative shock identifications: Baseline vs Scheme II: sign and narrative



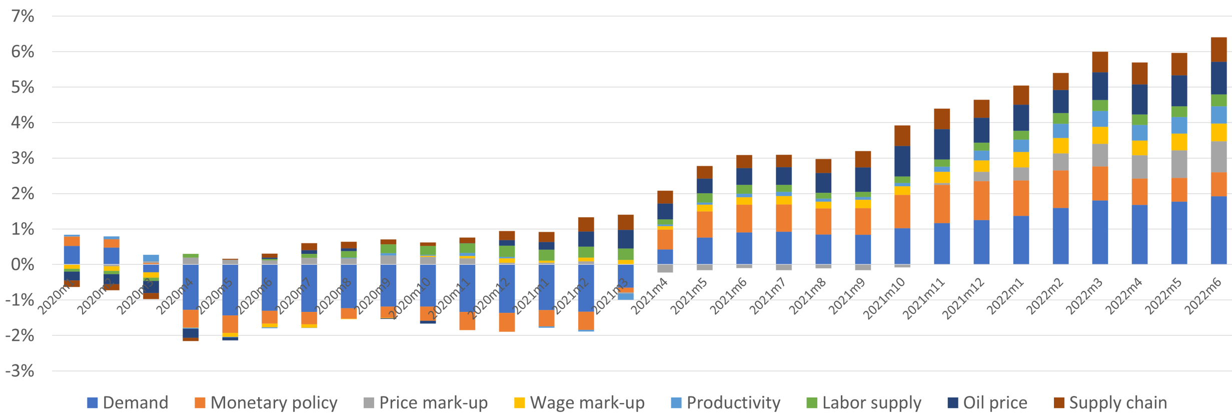
Notes: This figure plots responses to 1 standard deviation shocks in two different identification schemes: Baseline and Scheme II. The baseline identification scheme, where sign, narrative, and FEVD restrictions are employed, is in blue and Scheme II, where sign and narrative restrictions are utilized, is in red. Solid lines represent median responses and shaded regions correspond to 68% confidence bands. Variables are in the rows and shocks are in the columns. The responses are traced over 24 months. GDP is the logarithm of the real gross domestic product; CPI is the logarithm of the consumer price index; FFR is the effective federal funds rate; WAGE is the logarithm of the real wages; HOUR is the logarithm of the total hours; PR is the labor force participation rate; WTI is the logarithm of the West Texas Intermediate crude oil price; GSCPI is the Global Supply Chain Pressure Index.

Figure A.5: IRF comparison with alternative shock identifications: Baseline vs Scheme III: sign and FEVD



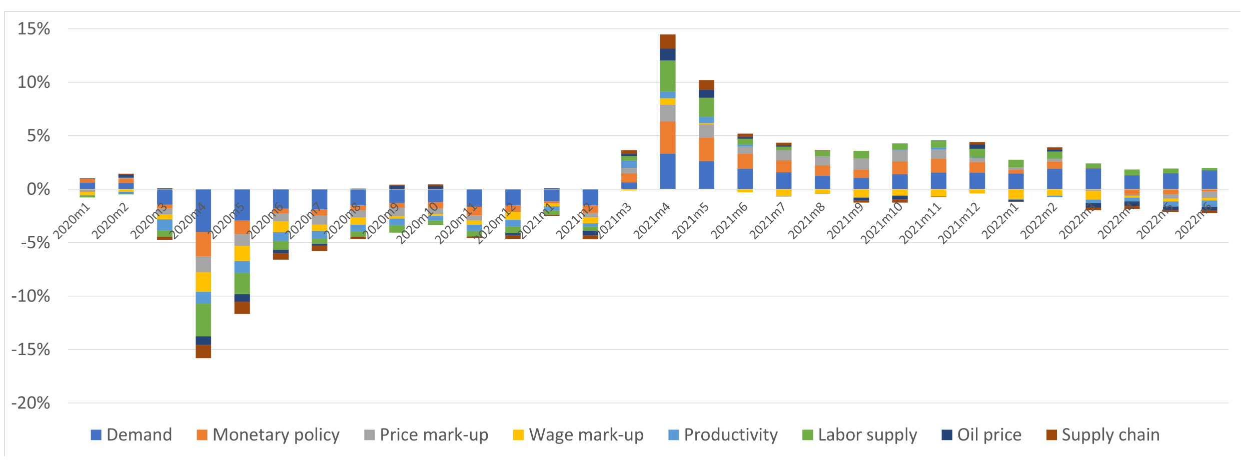
Notes: This figure plots responses to 1 standard deviation shocks in two different identification schemes: Baseline and Scheme III. The baseline identification scheme, where sign, narrative, and FEVD restrictions are employed, is in blue and Scheme III, where sign and FEVD restrictions are utilized, is in red. Solid lines represent median responses and shaded regions correspond to 68% confidence bands. Variables are in the rows and shocks are in the columns. The responses are traced over 24 months. GDP is the logarithm of the real gross domestic product; CPI is the logarithm of the consumer price index; FFR is the effective federal funds rate; WAGE is the logarithm of the real wages; HOUR is the logarithm of the total hours; PR is the labor force participation rate; WTI is the logarithm of the West Texas Intermediate crude oil price; GSCPI is the Global Supply Chain Pressure Index.

Figure A.6: Historical decomposition of inflation (year-over-year) under identification Scheme I: sign



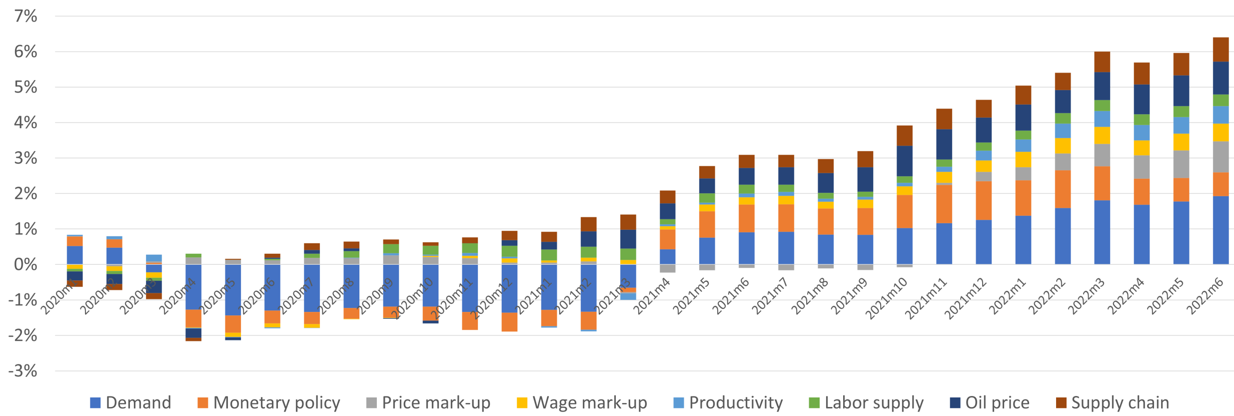
Notes: The figure presents the contribution of each structural shock to the deviation of inflation rate from its steady state, that is, the rate implied by the model with initial conditions and no shocks. The steady-state year-over-year inflation is found to be around 2.3% and stable over time. The structural shocks are obtained from Scheme I, where only sign restrictions are employed.

Figure A.7: Historical decomposition of output growth (year-over-year) under identification Scheme I: sign



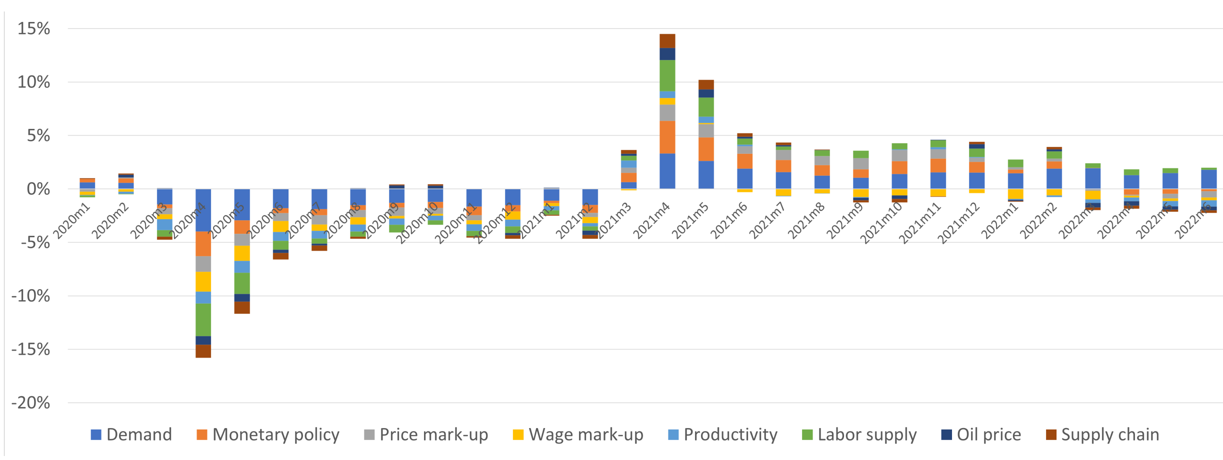
Notes: The figure presents the contributions of structural shocks to the deviation of growth rate of output from its steady state, thus, the rate implied by the model with initial conditions and no shocks. The steady-state year-over-year growth rate is found to be around 1.9% and stable over time. The structural shocks are obtained from Scheme I, where only sign restrictions are employed.

Figure A.8: Historical decomposition of inflation (year-over-year) under identification Scheme II: sign and narrative



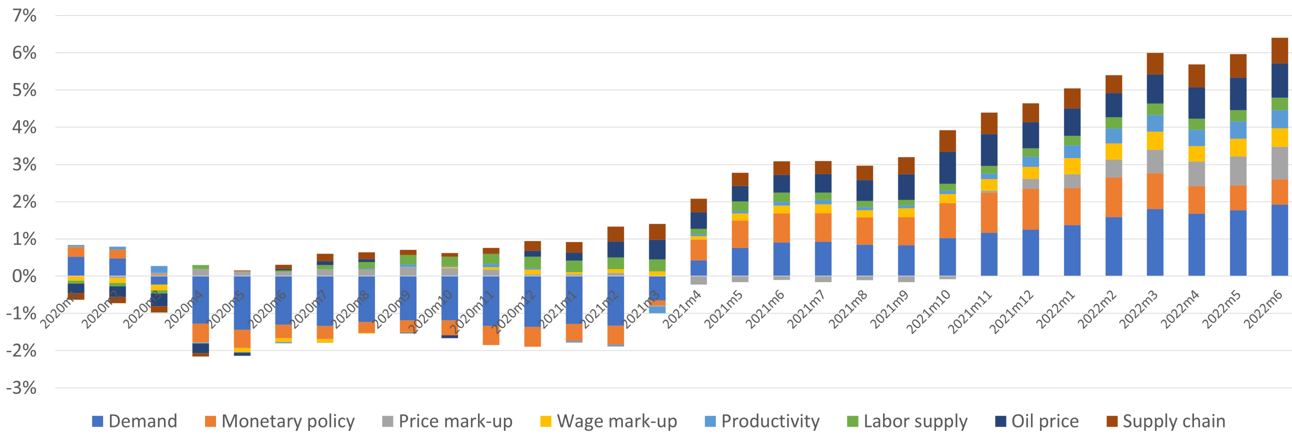
Notes: The figure presents the contribution of each structural shock to the deviation of inflation rate from its steady state, that is, the rate implied by the model with initial conditions and no shocks. The steady-state year-over-year inflation is found to be around 2.3% and stable over time. The structural shocks are obtained from Scheme II, where sign and narrative restrictions are employed.

Figure A.9: Historical decomposition of output growth (year-over-year) under identification Scheme II: sign and narrative



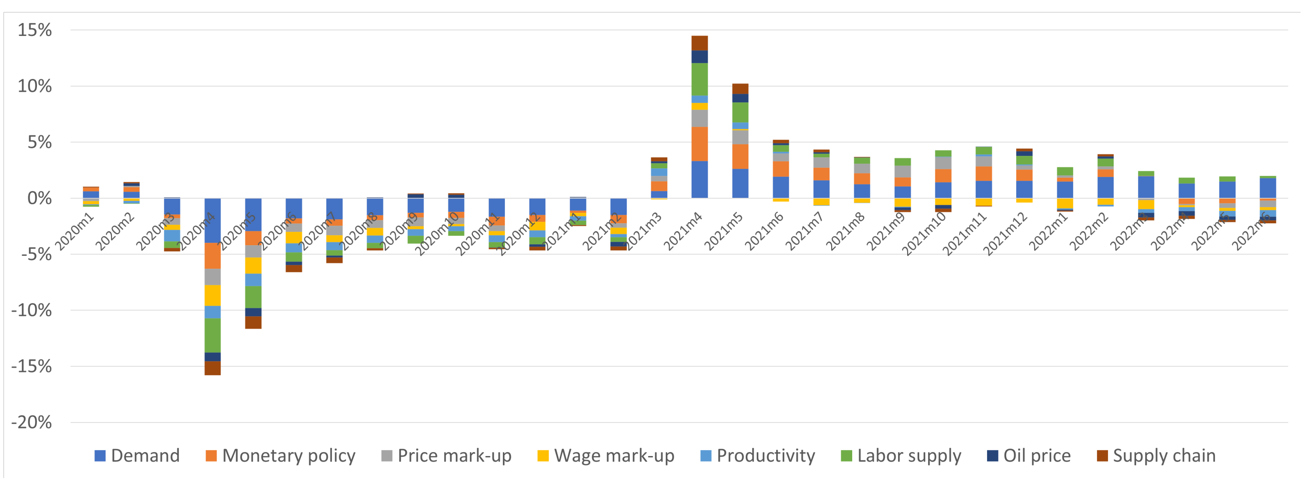
Notes: The figure presents the contributions of structural shocks to the deviation of growth rate of output from its steady state, that is, the rate implied by the model with initial conditions and no shocks. The steady-state year-over-year growth rate is found to be around 1.9% and stable over time. The structural shocks are obtained from Scheme II, where sign and narrative restrictions are employed.

Figure A.10: Historical decomposition of inflation (year-over-year) under identification Scheme III: sign and FEVD



Notes: The figure presents the contribution of each structural shock to the deviation of inflation rate from its steady state, that is, the rate implied by the model with initial conditions and no shocks. The steady-state year-over-year inflation is found to be around 2.3% and stable over time. The structural shocks are obtained from Scheme III, where sign and FEVD restrictions are employed.

Figure A.11: Historical decomposition of output growth (year-over-year) under identification Scheme III: sign and FEVD



Notes: The figure presents the contributions of structural shocks to the deviation of growth rate of output from its steady state, that is, the rate implied by the model with initial conditions and no shocks. The steady-state year-over-year growth rate is found to be around 1.9% and stable over time. The structural shocks are obtained from Scheme III, where sign and FEVD restrictions are employed.