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Supply shocks and inflation: timely insights from financial markets

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Abstract

We introduce a mixed-frequency model that identifies the impact of supply shocks on inflation in the United States in real time. The model decomposes weekly movements in inflation-linked swap rates—market-based inflation expectations—and isolates three supply shocks: global value chain disruptions, energy supply shocks, and domestic supply constraints, separating them from demand-driven factors. We show how these shocks contributed to a post-Covid feedback loop that intensified inflation. By linking weekly shocks to monthly inflation components up to the industry level, we find that global value chain disruptions generate the most persistent and broad-based price pressures, while energy and domestic supply shocks tend to produce more transitory effects, as their narrower inflationary impact is more easily offset by demand-dampening, contractionary forces. Our model captures these various supply-side dynamics effectively and offers timely insights to support a more responsive monetary policy.

Keywords: Supply Shocks, Mixed-frequency VAR, Inflation

JEL Codes: C54, C58, E31, G12, G15.

Non-Technical Summary

In the wake of the Covid-19 pandemic, inflation in the United States rose to levels not seen in decades. Understanding the causes of this inflation surge was crucial for policymakers, as mistimed or misdirected actions—such as raising interest rates too soon or maintaining too much stimulus—could have stalled the economic recovery. This paper focuses on one major source of inflation during this time: supply shocks. These include disruptions in global supply chains, shortages in the labour market, and volatility in energy markets.

To help policymakers respond more effectively, the paper introduces a new analytical framework that tracks inflation drivers on a weekly basis using market-based measures—specifically, inflation-linked swap (ILS) rates. These financial instruments offer real-time insights into inflation expectations and tend to be more responsive than traditional surveys. The framework combines fast-moving financial data with slower-moving economic indicators to identify five key drivers of inflation: two related to demand (overall economic demand and monetary policy) and three related to supply (global supply chain disruptions, energy shocks, and domestic supply constraints).

The findings show that different types of supply shocks affect inflation in very different ways. Energy shocks tend to be short-lived and mostly affect the energy component of consumer prices. Domestic supply shocks—often linked to labour shortages—have a stronger, albeit temporary, impact on core inflation, as their effects are partly offset by slower economic growth. In contrast, global supply chain disruptions have the most persistent and broad-based effects, influencing multiple sectors and taking longer to resolve. These extended disruptions make it more challenging for inflation to return to target levels and demand more proactive and nuanced policy responses.

Our study shows that central banks cannot treat all supply shocks the same. While temporary energy price spikes can often be "looked through", supply chain and labour-related disruptions might require more immediate and targeted interventions. By identifying the sources of inflation pressure in near real time, the proposed framework gives policymakers a tool to balance the goals of stabilizing inflation and supporting economic growth—especially during periods of economic turbulence like the Covid-19 pandemic.

1 Introduction

The surge in inflation experienced in the United States (US) during the aftermath of the Covid-19 pandemic reached levels not seen in decades, prompting urgent scrutiny of its underlying causes. Among the various contributing factors, supply shocks—stemming from disrupted global supply chains, labour shortages, and turmoil in energy markets—played a critical role in driving prices higher (Ball et al., 2022; Blanchard and Bernanke, 2024; De Santis, 2024). Assessing the relative impact of these supply-side disturbances, as opposed to demand-driven pressures, became essential for policymakers to respond effectively. Accurate and timely identification of the primary inflation drivers was crucial to prevent policy missteps—such as premature tightening or excessive stimulus—that could have either exacerbated inflationary pressures or stall the economic recovery. This paper examines the pivotal role of supply shocks in the recent inflationary episode and presents a modelling framework to more promptly identify the drivers of US inflation, thereby supporting effective monetary policy. We do that by analysing the drivers of market-based inflation expectations.

Inflation expectations serve as a cornerstone of macroeconomic theory and policy. They shape real interest rates and, in turn, influence a wide range of economic behaviours, including households' consumption decisions, labour market dynamics, and firms' pricing and investment strategies (Carlson and Parkin, 1975). Central banks rely on well-anchored inflation expectations to effectively manage real interest rates, especially under constraints such as the effective lower bound on nominal policy rates (Galí, 2015).

Yet policy makers face challenges when relying on measures of inflation expectations to inform policy decisions. Inflation expectations vary widely across economic agents: while professionals and markets show anchored views, households and firms exhibit greater volatility, more disagreement, and reliance on past prices (Candia et al., 2024; Candia et al., 2024; Di Pace et al., 2024; Allayioti et al., 2024; D'Acunto et al., 2023). This heterogeneity complicates effective policy design, as shown in Coibion et al. (2020), especially in periods of high uncertainty, when inflation expectations strongly influence the behaviour of economic agents and may diverge from policymakers' targets. A timely indicator of inflation expectations is therefore essential, and it is unclear whether survey-based measures capture these in a sufficiently forward-looking and timely manner.

A popular complement to survey-based measures are therefore inflation expectations derived from financial markets, such as inflation-linked swap (ILS) rates. These are derivative contracts to hedge or gain exposure to inflation risk. These measures have several appealing features: they are available at high frequency, do not share many survey-based measurement issues[1], and they timely and efficiently incorporate new information, as long as markets are liquid. Moreover, market-based measures often outperform survey data in correlating with future inflation trends (Boeckx et al., 2024; Campbell et al., 2023). Correlating ILS rates with realized inflation shows that they are indeed a good predictor for realized price movements, see Figure 1, in line with Campbell et al. (2023). As an illustration, the regression coefficient of the 1-year 1-year (1Y1Y) ILS rate on realized inflation peaks near 1 between one and two years ahead, when inflation and expectations align. This exceeds coefficients derived from survey-based measures, such as the Michigan survey or the Cleveland Fed index, which aggregates multiple inflation indicators like Blue Chips.[2] ILS rates also account for a much larger share of realized inflation variance than these other measures, particularly over horizons up to two years. While a drawback of market-based ILS rates is the inclusion of risk premia, these tend to be very small for the short maturities we consider, as illustrated by Cuciniello (2024), and are shown to generally correlate with "genuine" inflation expectations.[3]

Despite their appealing properties, there is limited research on the reaction of market-based inflation expectations to structural shocks. Integrating real-time insights into whether expectations are driven by demand or supply is crucial for informed policy decisions, particularly in the context of major global disruptions, and given the lags in monetary policy transmission. Indeed, what was initially seen as a temporary, supply-driven price spike in inflation following the Covid-19 outbreak evolved into persistent, record-high inflation, fundamentally altering the challenges faced by policymakers. This experience has also showcased how the reaction of aggregate prices to supply-side fluctuations drastically depends on the nature of the shock. Energy supply shocks, for example, tend to be short-lived[4], while global supply shocks—often related to disruptions in the

[1] Such as being backward-looking or overly sensitive to specific price sub-components.

[2] The Cleveland Fed inflation expectation index combines data from Blue Chips, Bloomberg, the Bureau of Labor Statistics, the Philadelphia Fed, the Fed Board, and Haver. See Haubrich et al. (2012).

[3] Cuciniello (2024) uses a standard term structure model to decompose ILS rates at different horizons into pure inflation expectations and risk premia components, showing that risk premia in ILS rates are small at short horizons (up to three years).

[4] For euro area inflation, however, Adolfsen et al. (2024) demonstrate that gas supply shock, such as those experienced in context of the Russian invasion of Ukraine, have significantly fed through core inflation in the euro area, thereby creating persistent inflationary effects.

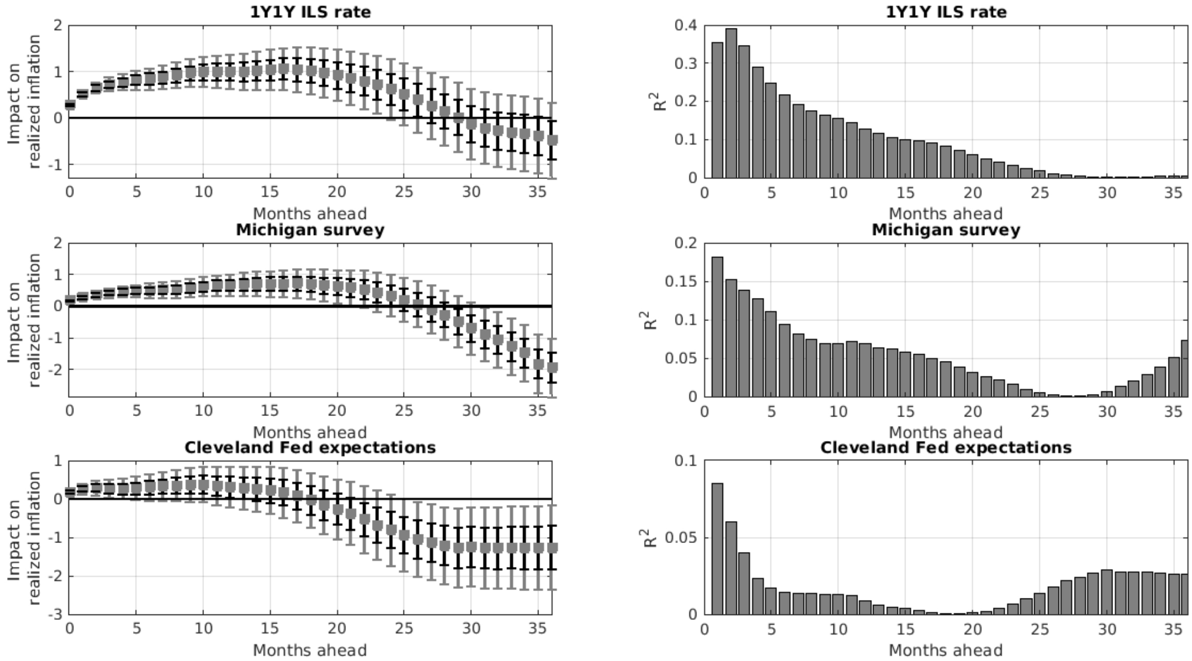

Figure 1: Explanatory power of ILS rates versus survey-based measures for US inflation.
Notes: the figure reports the β coefficient and the R^2 of the regression $\pi_{t-1,t+k} = \alpha + \beta ILS_t + \epsilon_t$ (upper row) and $\pi_{t-1,t+k} = \alpha + \beta Survey_t + \epsilon_t$ (bottom two rows), where ILS is the 1Y1Y US ILS rate, $Survey$ is either the one-year ahead Michigan inflation survey or the Federal Reserve Bank of Cleveland's expected inflation rate. The dependent variable is realized US CPI inflation between periods $t-1$ and $t+k$. The regression is estimated at monthly frequency. The vertical lines show 95% and 68% confidence intervals.

global value chain—have long-lasting effects, see Ascari et al. (2024), Bai et al. (2024), Comin et al. (2023), and Arce et al. (2024).[5] Extracting information on the origin of supply fluctuations from market-based data could therefore help in the timely calibration of policy responses.

Modelling higher-frequency supply shocks presents several difficulties, however. Measures of pure supply-side pressures are limited at frequencies higher than monthly, which poses a challenge for timely identification. Also instruments for specific supply shocks—such as disruptions to the global value chain—are not available at such frequencies. Concerning identification, different types of supply shocks often move ILS rates and other financial market variables in similar directions, making it difficult to identify these shocks through the use of sign restrictions—which is commonly used when disentangling higher-frequency financial market movements, as for instance in Brandt et al. (2026).[6]

To overcome these issues, we rely on a mixed-frequency approach using lower-frequency,

[5]Recent research has also shown how different types of energy shocks (for example, in the oil or gas market) have different impacts on inflation, Adolfsen et al. (2024).

[6]Complementing a high-frequency identification scheme with narrative restrictions is a possibility, but it relies on the assumption that a limited number of events can adequately represent dynamics across the full sample.

monthly data to discipline the identification of shocks at the higher, weekly frequency.[7] Our model includes four high-frequency financial market variables (US 10-year yields, 1-year 1-year ILS rates, S&P 500 and energy prices) and two low-frequency monthly variables (US industrial production and the global supply chain pressure index by Benigno et al., 2022). We separate five structural drivers of ILS rates using a combination of sign and narrative restrictions: two demand-side shocks—aggregate demand and monetary policy—and three supply-side shocks—global value chain (GVC), energy, and domestic supply shocks. This approach enables us to uncover the underlying forces behind surges in inflation expectations, such as observed following the Covid-19 pandemic. By linking the estimated weekly demand and supply shocks to monthly inflation in a second step, we further identify the specific inflation dynamics each type of shock generates, as well as the early signals they convey for expected inflation.

Two findings are worth highlighting. First, different types of supply shocks have vastly different effects on US inflation, necessitating tailored responses in monetary policy. Energy supply shocks typically have a short-lived impact on headline consumer prices, as their inflationary effects are narrow and tend to have limited pass-through to other prices. This dynamic allows the contractionary effects of higher energy costs to outweigh their direct contribution to overall price levels. Domestic supply shocks, by contrast, primarily operate through the labour market and can lead to significant pass-through to core inflation. However, this effect is also mitigated by the restraining impact such shocks have on economic growth. The inflationary impact of GVC shocks, by comparison, is more broad-based, stronger and lasts longer. This is as disruptions in global supply constraints affect all price indices as the supply of core inputs needed at all stages of production is constrained, reducing the productive capacity of firms. As production is constrained, prices must clear the market, as outlined in recent theoretical (Comin et al., 2023) and empirical evidence (De Santis, 2024; Ascari et al., 2024). It also takes more time for the price pressures to fade following GVC shocks, due to the broad-based nature of the price increase. For instance, after a domestic supply shock, energy prices typically fall, easing the contraction in real output and aiding the recovery. However, during a GVC shock, input scarcity also affects energy producers, preventing energy prices from dropping. This disrupts a key mechanism that would otherwise mute inflationary pressures and support

[7] This is similar in spirit to Gazzani et al. (2024) who use the response of monthly variables to select daily oil market shocks

the economic recovery. These results remain robust when the post-pandemic years are excluded from the sample.

This finding carries important policy implications. While the traditional approach of "looking through" supply shocks (Blanchard and Gali, 2007) is appropriate for energy supply shocks, it is less applicable to domestic supply shocks and even less so for disruptions originating in global value chains. In such cases, the trade-off between stabilizing output and inflation becomes more acute, potentially requiring a more aggressive policy response.

The second main finding is that our proposed modelling framework provides an effective and timely identification of the source of the shock at weekly frequency, making it a valuable tool for timely analysis of the drivers of US inflation. When applied to the Covid-19 pandemic and recovery, the model highlights the unprecedented combination of various demand and supply shocks that drove inflation expectations to historic highs. During the Covid-19 outbreak, collapsing demand kept market-based inflation expectations low, despite significant monetary stimulus and growing supply chain pressures. As the economy began to recover, GVC pressures took centre stage, driving inflation expectations higher together with domestic supply shocks reflecting labour supply constraints. By mid-2022, easing GVC bottlenecks, combined with the onset of monetary policy tightening, helped bring expectations back down. This intricate interplay of shocks, tracked on a weekly basis, underscores the value of the framework in supporting policymakers' decisions during challenging times.

Related literature: Our paper contributes to several strands of the literature. First, several papers have examined the forecasting properties of ILS rates: Carlson and Parkin (1975), Coibion et al. (2020), Duca et al. (2018), Coibion et al. (2018), D'Acunto et al. (2023), Campbell et al. (2023), and Boeckx et al. (2024). These studies show that ILS rates have strong forecasting properties for actual inflation. We build on these findings to extract timely information on the drivers of inflation in the US through ILS rates. The closest to our work is Höynck and Rossi (2023), who identify drivers of ILS rates at a daily frequency. Unlike their approach, we exploit the mixed-frequency structure of our model to identify supply shocks at a higher frequency, using variables like the global supply chain pressure index that are orthogonal to demand and domestic shocks, rather than relying on a limited set of narrative restrictions in historical decompositions. Another strand of literature this paper relates to is the identification of supply shocks. A growing number of studies have looked at how different types of supply shocks affect the real economy. These include Eickmeier and Ng (2015), who analyze the global diffusion of US supply shocks; Cashin et al. (2014) and De Santis (2024), who disentangle the role of energy supply shocks; Guerrieri et al. (2022), who study Keynesian supply shocks; and Eickmeier and Hofmann (2022), who disentangle supply and demand factors for the US and the euro area. Fornaro and Wolf (2023) explores supply disruptions in an economy with Keynesian unemployment and endogenous productivity growth, showing that scarring effects depress demand and equilibrium interest rates and amplifying the rise in inflation. Others have focussed on measuring supply disruptions, with Bai et al. (2024) and Benigno et al. (2022) developing alternative measures of global supply chain pressures. Finally, Ascari et al. (2024) considers the role of shocks to the global value chain on macroeconomic outcomes. From a technical perspective, our work is related to the literature on identification in VARs with mixed frequency, including Schorfheide and Song (2015), Antolín-Díaz and Rubio-Ramírez (2018), Arias et al. (2018), Ferroni and Canova (2021), Consolo et al. (2023), and Gazzani et al. (2024).[8] Relative to these contributions, this paper is the first to disentangle different sources of supply shocks using financial market data at higher, weekly frequency. In doing so, we extend the current literature by connecting signals from financial markets with the real economy.

2 Data and Methodology

Our mixed-frequency VAR model aims to identify the structural shocks driving market-based inflation expectations at a weekly frequency, combining higher-frequency financial market data with lower-frequency macro data, such as industrial production and supply chain pressures, to inform shock identification. In the second step we examine how these shocks affect actual inflation in the US using local projections, with a two-step procedure similar to Adolfsen et al. (2024), Dedola et al. (2017), Iacoviello and Navarro (2019) and

[8] Gazzani et al. (2024) relies on local projections of the (aggregated) high-frequency shocks on low-frequency macro variables to restrict the identification, while this paper jointly uses low- and high-frequency data within a unified VAR framework. In other words, Gazzani et al. (2024) restricts the parameter space by taking candidate shocks outside the VAR model, while our approach relies on a unified framework in which information from low-frequency variables is incorporated into the estimation of the model's parameters and the restrictions on the shocks.

Debortoli et al. (2023).

Specifically, the VAR model includes four high-frequency (weekly) financial market variables and two low-frequency (monthly) variables, and it identifies five key shocks. The weekly variables are: the 10-year US Treasury bond yield,[9] 1-year forward inflation-linked swaps one year ahead (1Y1Y ILS hereafter), the S&P 500 index, and an energy price index.[10] At the maturity we consider, the risk premia in ILS rates are, on average, small, as shown by Cuciniello (2024). The financial market variables are complemented by monthly data capturing global value chain disruptions and economic activity: the New York Fed's Global Supply Chain Pressure (GSCP) Index by Benigno et al. (2022) and US industrial production. CPI is not included in the model directly to avoid imposing restriction on the reaction of prices to the identified shocks. This allows to use the identified shocks in Section 4 to compute the responses of prices through local projections. The exercise is not only useful to validate the model ex-post but also sheds light on the transmission channels of shocks to inflation that do not depend on imposed restrictions on CPI movements.

The GSCP Index helps identify "pure" global supply shocks, which are generally hard to disentangle using financial market data alone.[11] The advantage of the GSCP Index is that it combines several global supply-side variables, such as supply-related PMIs, delivery times, and transportation costs, into a single measure. Importantly, before aggregation, the underlying data are purged of demand components and domestic developments. This implies that changes in the GSCP Index reflect only global supply pressures, see Benigno et al. (2022), which is key to our identification strategy. The intuition is the following: because the GSCP Index primarily reflects global value chain disruptions, we use it to identify a "global value chain" shock—defined as a price shock resulting from disruptions

[9]Results are stable when using the 2-year yield, see Appendix C.1. The 10-year is preferable as it also captures changes at the long end of the yield curve relevant when monetary policy is conducted with unconventional tools such as asset purchases.

[10]For the energy price, we use the Goldman Sachs Energy Index, a sub-index of the Goldman Sachs Commodity Index. The Index is calculated using the most recent prices of liquid commodity futures contracts. Prices are multiplied by their world production weights and divided by a normalizing constant that relates an index to a base period. Commodities included are crude oil, Brent crude, unleaded gasoline, heating oil, gasoil, natural gas.

[11]Financial variables like yields, stock prices, and ILS rates tend to react similarly to different supply shocks—perhaps with the exception of energy price shocks as these are typically contractionary and tend to increase inflation expectations. Höynck and Rossi (2023) address this identification problem using narrative restrictions, but that approach relies on a limited number of events to inform the identification of the model. We take a different path and instead exploit the informational content of a pure global supply-side indicator.

in the flow of inputs and outputs across the global trade network. We further use energy prices to identify energy price shocks, and finally, domestic supply shocks are the supply component orthogonal to both global value chain and energy shocks. Because the GSCP Index is constructed at a monthly frequency, mixed-frequency methods are necessary for its use in the identification for higher-frequency shocks.

Given its centrality to the identification of the GVC shock, we test the exogeneity of the GSCP Index to demand-side and domestic developments. We do so by regressing the index on global and US industrial production, formally:

$$\Delta GSCPI_t = \alpha + \beta_0 \Delta IP_t + \sum_{l=1}^{L} \beta_l \Delta IP_{t-l} + \epsilon_t \tag{1}$$

where, ΔIP denotes the log-change of US or world industrial production. If demand-side and domestic shocks influence the index, then present or past values of industrial production should predict it. Table 1 shows that lags of industrial production do not systematically predict changes in the GSCP Index; moreover, up to six lags of industrial production explain only a negligible share of its volatility (at most 3%). Similar results are obtained when financial variables such as the VIX index, the S&P 500, or the US 10-year yield are used as controls; see Table A.1 in the Appendix. These results support our identification strategy of using the GSCP Index as a proxy for supply shocks.

Table 1: Predictability of the GSCP Index

	US industrial production							Global industrial production						
	$L=0$	$L=1$	$L=2$	$L=3$	$L=4$	$L=5$	$L=6$	$L=0$	$L=1$	$L=2$	$L=3$	$L=4$	$L=5$	$L=6$
β_0	-10.62	-9.46	-14.09	-11.77	-14.24	-1.88	-11.22	10.96	13.60	10.80	11.78	9.35	8.06	6.66
	(0.89)	(0.90)	(0.86)	(0.88)	(0.86)	(0.98)	(0.89)	(0.90)	(0.88)	(0.91)	(0.90)	(0.92)	(0.93)	(0.94)
β_1		-7.96	-5.08	-10.30	-7.36	-12.74	2.00		3.46	5.77	2.33	3.78	1.68	0.85
		(0.92)	(0.95)	(0.90)	(0.93)	(0.88)	(0.98)		(0.97)	(0.95)	(0.98)	(0.97)	(0.99)	(0.99
β_2			-11.96	-8.56	-13.85	-8.43	-15.86			7.71	11.17	7.67	9.02	6.73
			(0.88)	(0.92)	(0.87)	(0.92)	(0.85)			(0.93)	(0.91)	(0.94)	(0.93)	(0.95)
β_3				-12.09	-9.20	-14.78	-9.32				3.90	7.05	3.66	5.15
				(0.88)	(0.91)	(0.86)	(0.91)				(0.97)	(0.94)	(0.97)	(0.96)
β_4					-9.94	-6.83	-11.65					6.12	9.37	5.92
					(0.90)	(0.93)	(0.89)					(0.95)	(0.92)	(0.95)
β_5						-12.20	-9.67						5.47	8.52
						(0.88)	(0.91)						(0.95)	(0.93)
β_6							-9.19							0.11
							(0.91)							(0.95)
Adj. R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N	226	225	224	223	222	221	220	225	224	223	222	221	220	219

Notes: the table reports parameter estimates for Equation (1). P-values are reported in parenthesis below coefficients along with the adjusted R^2. Industrial production enters the regression in log-changes, while the GSCP Index in simple changes.

All variables enter the model in log-changes with the exception of yields and the GSCP

Index which enter as simple differences. Summary statistics for the six endogenous variables, in changes, are reported in Table 2 while data (in levels) are plotted in Figure B.1. Notice that the energy price index is significantly more volatile than the other financial variables, leading to stronger impulse responses as shown in Section 3.1.

Table 2: Summary statistics

	10-year yield	1y1y ILS	S&P500	Energy price	GSCP	US IP
Mean	-0.0001	-0.0003	0.158	0.019	0.003	0.030
Std deviation	0.098	0.150	1.931	3.873	40.860	1.302
Frequency	weekly	weekly	weekly	weekly	monthly	monthly
Sample start	2005w16	2005w16	2005w16	2005w16	2005M4	2005M4
Sample end	2025w6	2025w6	2025w6	2025w6	2025M2	2025M2

Notes: the table reports summary statistics for percent changes in the 10-year US yield and 1Y1Y ILS, 100× log changes for the S&P500 index, the energy price index and US industrial production and differences in the GSCP Index.

3 Mixed-frequency VAR model

Low- and high-frequency data are combined using the mixed-frequency Bayesian VAR framework developed by Eraker et al. (2014), Ghysels (2016), and Schorfheide and Song (2015). The identification of key shocks driving ILS rates is based on a mix of sign and narrative restrictions, leveraging the mixed-frequency nature of the data and the exogeneity of the GSCP Index with respect to global demand and domestic factors. The low-frequency component of the model—particularly the GSCP Index—acts as a constraint on the identified shocks and enables the identification of global value chain disruptions that are orthogonal to other supply-side shocks, similarly to Gazzani et al. (2024).

The mixed-frequency model combines weekly financial variables ($y^w t$) with two monthly variables ($y^m t$): the GSCP Index and US industrial production. The model can be written in state-space form as:

$$
\begin{aligned}
\begin{bmatrix} x_t^w \\ x_t^m \end{bmatrix} &= A_0 + \sum_{l=1}^{L} A_l \begin{bmatrix} x_{t-l}^w \\ x_{t-l}^m \end{bmatrix} + B\epsilon_t \\
y_t^w &= x_t^w \\
y_t^m &= \frac{1}{4}\sum_{i=0}^{3}\left(x_{t-i}^w\right)
\end{aligned}
\tag{2}
$$

Here, A_0 and A_l are matrices of reduced-form parameters. x^m represents the weekly observations of the monthly variables, which are produced using a Kalman filter for a given draw of the model's parameters. B is a matrix of contemporaneous relationships between the shocks ϵ_t and the endogenous variables. Sign and narrative restrictions are used to identify elements in the matrix B, in the spirit of Arias et al. (2018), Uhlig (2017), and Antolín-Díaz and Rubio-Ramírez (2018). The model is estimated using a standard Minnesota prior, with hyperparameters selected as in Giannone et al. (2015). A key challenge for estimation is the Covid-19 period (from March to December 2020), which presents exceptional volatility in both financial markets and the global trade network; see Figure B.1. Following Lenza and Primiceri (2022), these observations are not excluded from the sample but are instead discounted to prevent them from biasing the parameter estimates—which should reflect long-run relationships rather than short-term (abnormal) volatility. The weekly filtered series for the monhtly GSPC Index and industrial production are plotted in Figure B.2 and Figure B.3, respectively.

The main characteristic of the identification strategy is the application of a mixed-frequency methodology to guide the high-frequency identification of supply shocks. This approach combines the "best of both worlds", as the information content of macroeconomic variables is used to filter out different drivers of fluctuations in ILS rates. Global value chain (GVC) shocks—price pressures resulting from disruptions in the flow of intermediate inputs across the global trade network—are identified using the GSCP Index, as this variable is not contemporaneously affected by other demand or domestic shocks. The other two supply shocks—a domestic supply shock and an energy price shock—are identified separately and therefore orthogonal to the GVC shock. Implicitly, this defines the GVC shock as unrelated to higher energy costs that makes production more expensive for firms. Examples of such a shock could be the scarcity of semiconductors for technology firms or disruptions in the global trade network. While historically higher commodity prices have been the major source of supply-driven pressures (consider, for example, the oil crisis in the 1970s)[12], supply chain pressures have become more relevant in recent years. Recent research on the transmission of supply pressures, including Comin et al. (2023) and Bai et al. (2024), argues that these shocks can trigger scarcity and nonlinear effects, resulting in sharp price increases.[13] Distinguishing between these two channels becomes even more relevant during periods of tight commodity markets and supply bottlenecks, such as the post-Covid-19 crisis, where they could reinforce each other's impact on inflation and expectations.

To separate the five structural shocks of interest, sign and zero restrictions are used as reported in Table 3 — where all shocks are defined as contractionary.

Table 3: Sign restriction table

	Macro shock	Monetary policy shock	Energy supply shock	GVC supply shock	Domestic supply shock	Unres. shock
US 10-year yield	-	+				
1y1y US ILS	-	-	+	+	+	
US equity	-	-	-	-	-	
Energy price	-		+		-	
GSCPI	0	0		+	0	
US IP	-	-	-	-	-	

Notes: "+" indicates a positive restriction on the response of the variable to the shock on impact; "-" a negative restriction; "0" a zero restriction on impact and empty cells indicate unrestricted responses.

Two types of domestic demand shocks are identified. First, a contractionary macro shock is assumed to reduce long-term yields, stock prices, industrial production, and energy prices on impact; inflation expectations also fall, due to lower aggregate demand and lower energy prices. Due to its broad definition, this shock likely captures multiple demand-side factors, such as shifts in consumption and investment preferences, aggregate government spending, and trade policy shocks. The second demand shock is a monetary

[12] See Blanchard and Galí (2009), Nakov and Pescatori (2010), and Filardo et al. (2020).

[13] The mechanism derived in the model by Comin et al. (2023) works as follows: when supply chains are disrupted, the maximum production capacity of firms shrinks, and firms cannot accommodate additional demand. Because production cannot expand, prices must clear the market, leading to strong inflationary pressures. In the model, this mechanism takes the form of an occasionally binding constraint on the pricing equation of firms—the Phillips curve of the model—that is triggered after shocks to the global supply of intermediates.

policy shock, with a tightening shock increasing yields, reducing equity prices and industrial production. As a result, inflation expectations are assumed to fall, in line with standard theory on the effects of monetary policy, while the reaction of energy prices is left unrestricted. These two demand shocks are separated from the supply shocks in the models through the GSCP Index. As this index is mostly driven by supply chain constraints and filtered from demand effects, as shown in Table 1, we impose a zero restriction on its contemporaneous reaction to demand shocks. In other words, demand shocks impact supply chains only indirectly, through their endogenous effects on production and yields.

In addition, three different types of supply shocks are identified. First, an energy price shock increases energy prices and, therefore, inflation expectations on impact, while it weighs on equity prices and output. The reaction of the GSCP Index is left unrestricted; higher energy prices could increase the tightness of global value chains by increasing transportation costs (which are part of the GSCP Index), although they could also alleviate pressures as lower production reduce import demand. The second supply shock is the GVC shock. A shock that tightens global value chains increases the GSCP Index and is contractionary, as it lowers equity prices and industrial production. However, it supports inflation expectations, as firms facing input constraints must clear demand through higher prices, see Comin et al. (2023). We separate this shock from the energy supply shock by assuming that energy prices only react with a lag to GVC shocks. Finally, we identify a standard supply shock, which absorbs supply-side fluctuations not related to GVC disruptions or energy supply shocks. This shock is assumed to raise ILS rates while lowering equity prices, industrial production and, consequently, energy prices. We impose that this shock affects the GSCP Index only with a lag to disentangle it from the GVC shock. A sixth shock is left unrestricted to capture other potential drivers of the included financial and macro variables. This shock will likely absorb low-frequency fluctuations in macro variables that are not captured by financial data alone, as well as risk factors we do not explicitly account for, such as shocks to inflation risk premia.

The identification is further strengthened by nine narrative restrictions, similar to those in Ascari et al. (2024) and Finck and Tillmann (2022), but applied to a weekly setting. Specifically, we impose: (i) global value chain shocks to have a contractionary effect during the weeks of the Tohoku earthquake in Japan (11 March 2011), the Ever Given blockade (23-29 March 2021), and the Shanghai Backlog (5 April 2022); (ii) energy supply shocks to be contractionary during the outbreak of the first and second Libyan Civil Wars (20 February 2011 and 18 May 2014) and in the week of the Russian invasion of Ukraine (24 February 2022); (iii) macro shocks to be contractionary during the first two weeks of the outbreak of the Covid-19 pandemic (23 February and 1 March 2020). These narrative restrictions are not required for identification, but they help reduce the uncertainty in the posterior shock distribution.

The model is robust to several perturbations around the baseline settings, as explained in Section 3.3 later on.

3.1 Impulse responses

When discussing the impulse responses, we focus on the three types of supply shocks—the newly estimated Global Value Chain (GVC) supply shock, the energy supply shock and the other, domestic supply shock—which are the primary shocks of interest in this paper. Impulse responses to macro and monetary policy shocks are presented in the Appendix for completeness. All responses are scaled to a one standard deviation shock.

Interestingly, the different supply shocks have quantitatively similar effects on ILS rates, which increase by between 3 and 7 basis points on impact, but the underlying economic mechanisms are vastly different. That is, the outcome is largely determined by how energy prices respond and interact with the downward pressures on output. A domestic supply shock increases inflation expectations and contracts real activity, but as energy prices endogenously fall, the impact on output, stock prices, and market-based inflation expectations is partially counterbalanced. A GVC shock is also contractionary but, importantly, energy prices do not decline following this shock. This likely occurs as the shock to global value chains increases the marginal cost of intermediate production, including energy. This disables a key endogenous mechanism that would normally cushion output losses—namely, the decline in energy costs—resulting in a much sharper contraction in production, with US industrial output falling by roughly three times as much. In turn, the final reaction of ILS rates is similar to that of a demand shock, as the initial, more broad-based price pressures are offset by larger output losses. Finally, the energy price shock stands in the middle: energy prices increase but less persistently than after a GVC shock as industrial production contracts, while also global supply chain pressures ease. In Section 4, we provide a more detailed analysis of the transmission mechanisms through which the various supply shocks affect CPI inflation. But first we discuss the impulse response functions in more detail below.

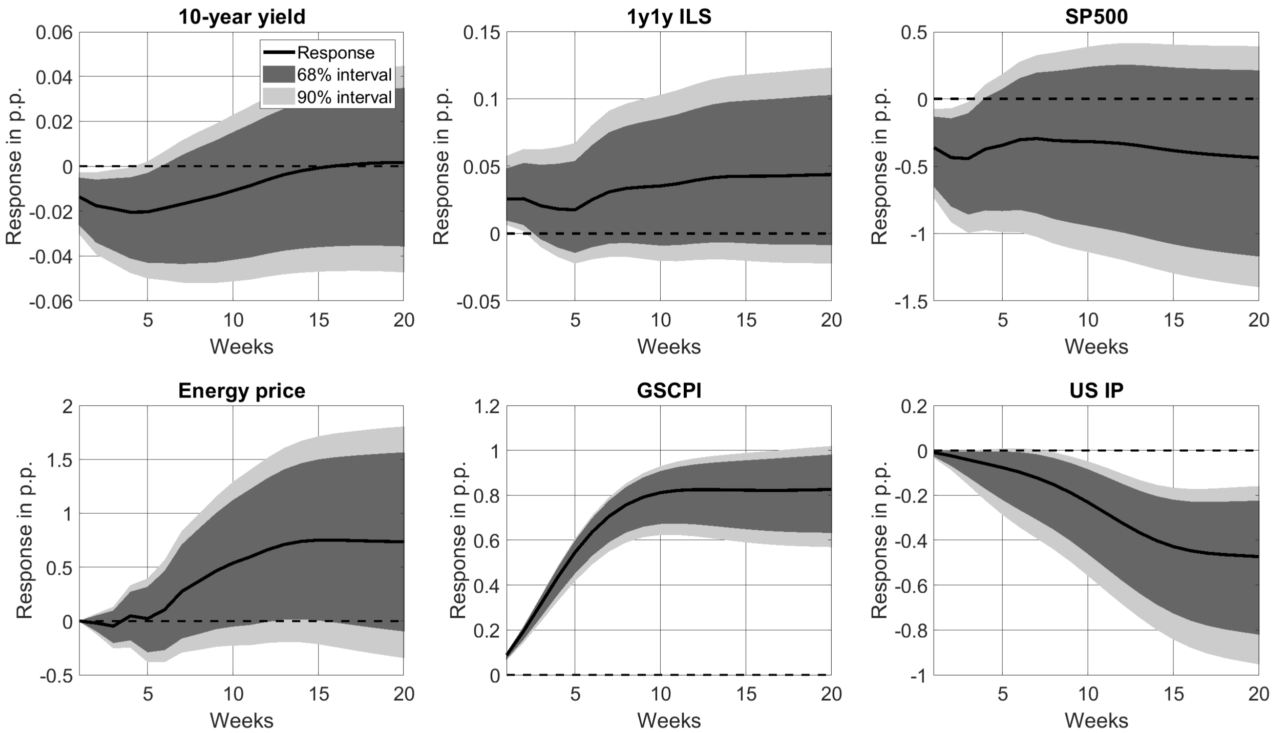

Figure 2: Impulse responses to a global value chain shock.
Notes: the figure reports the median (black solid line) response to a one standard deviation contractionary supply shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals.

Global Value Chain Shock; Figure 2 presents the cumulative impulse responses following a GVC shock. Several dynamics are worth highlighting. First, GVC shocks appear to be self-reinforcing, leading to a significant and gradually building impact on US industrial production. A one standard deviation shock increases the GSCP Index on impact by about 0.1 standard deviations which grows to 0.8 in the long run. These dynamics suggest that stress at one node of the global value chain delays input deliveries to downstream nodes, amplifying GVC tensions. Although the effect on stock prices becomes less certain after 4 weeks, GVC shocks cause a significant 70 basis point drop in US industrial production. As with the dynamics observed in the GSCP Index, the full impact on industrial production unfolds gradually over time. The elasticity of US industrial production to GVC shocks is about 0.87, which implies that the 4 standard deviation increase in global supply chain pressures observed during the pandemic contracted US industrial production by about 3.7 percentage points. This elasticity is close to the implicit elasticity of output to the supply chain index in Bai et al. (2024), which is 0.8. Second, energy prices are found to increase following a GVC shock, despite the fall in economic activity. This is likely as GVC shocks impair the flow of inputs across the global economy, impacting the energy production sector as well. If intermediate inputs and machinery are not timely available, energy production becomes scarcer, supporting the price despite lower real activity. This appears a key transmission channel of GVC shocks: unlike other supply shocks (which are all contractionary), energy prices do not fall endogenously and mitigate economic losses over the estimation horizon. This also underlines how disruptions in the global value chain generate compounding effects with spillovers across multiple sectors.

Energy supply shock; Energy shocks show a different profile, as shown in Figure 3. A one standard deviation shock leads to an increase in energy prices on impact. However, this reaction is short-lived, as the shock leads to a contraction in output, with industrial production falling by 0.5% after one month and about 1% in the longer term. The fall in industrial production translates into lower demand for energy, which endogenously reduces its price. Real losses are anticipated by stock prices, with the S&P 500 contracting by almost 0.5% on impact and by 1% after about two months. Weaker real activity also transmits to the global supply chain. As demand lowers, the GSCP Index decreases over time (by about 0.2 standard deviations after 8 weeks) because it becomes easier for suppliers to ship goods as trade volumes decline. As we left the reaction of the index unrestricted after this shock, this result provides clear evidence that the real effects dominate and ease supply chain constraints due to lower trade volumes, which puts downward pressure on 10-year yields.

Domestic supply shock; The reaction of ILS rates to domestic supply shocks is similar to that of a GVC shock as shown in Figure 4: they increase on impact by about 3 basis points and remain stable thereafter. However, the shock is much less contractionary in comparison to the other two types of supply shocks, with the median response of industrial production never going below -0.5% and quickly becoming statistically insignificant (after 4 weeks). This is also reflected in a weaker response of stock prices and the negative, mostly insignificant, impact on the GSCP Index. This result underpins the interpretation that these shocks remain "domestic" and do not meaningfully spill over to the global supply chain. Key to understanding the muted responses of these variables is

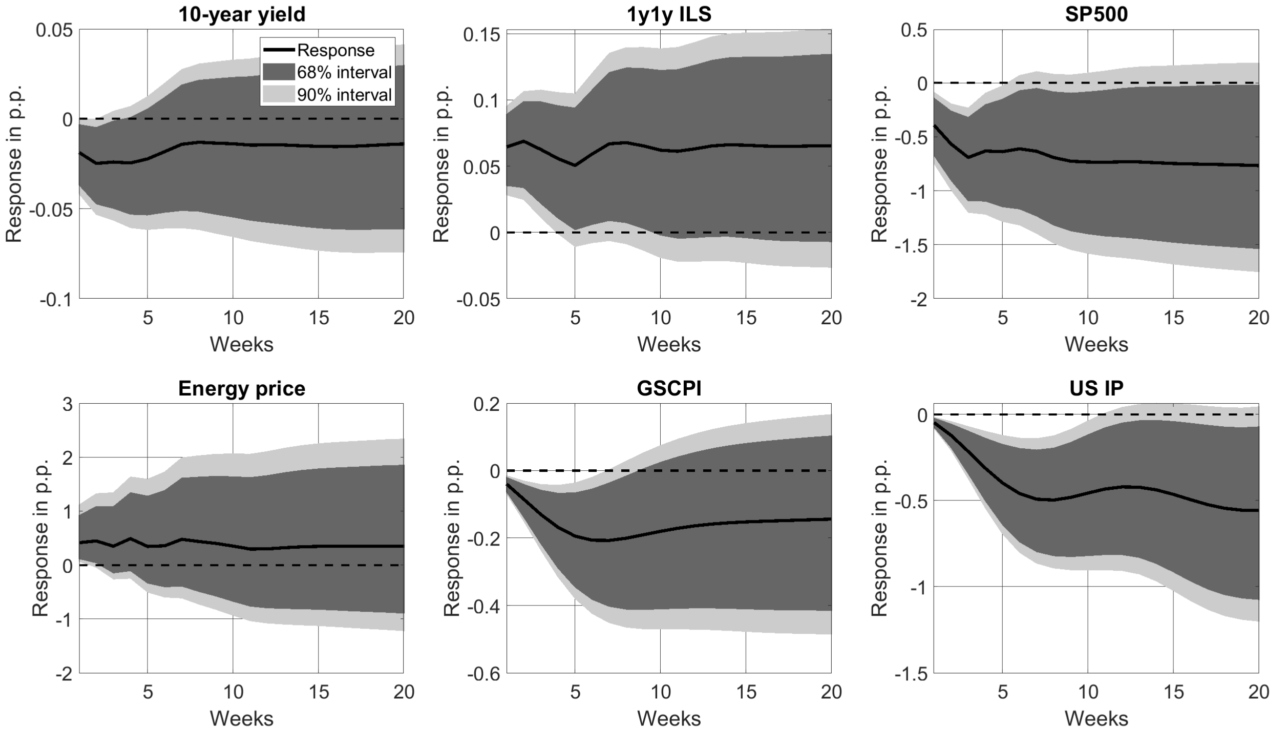

Figure 3: Impulse responses to a energy supply shock.
Notes: the figure reports the median (black solid line) response to a one standard deviation contractionary supply shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals.

the energy price index, which declines strongly and persistently (by about 2% on impact and remains subdued across the impulse response horizon). Energy prices are declining as domestic producers anticipate a drop in demand, despite no changes in the availability of energy imports or production equipment. This endogenous fall in energy prices dampens the impact on US industrial production and stock prices. Similarly, markets anticipate only a modest rise in future inflation, as the impact of the domestic supply shock on marginal production costs is offset by lower energy prices. Crucially, this does not hold after a GVC shock, where tightening supply chain constraints also drive up costs in the energy production sector — with more adverse effects on inflation as shown later on.

Demand shocks; The other two shocks—demand and monetary policy shocks—have more standard implications, as shown in Figure B.4 and Figure B.5. An aggregate macro shock, which in the model captures a broad range of demand-side developments[14], reduces US industrial production by 0.5% after one month and by approximately 1.5% in the

[14]These include, for example, changes in consumer preferences, investment, government spending, and trade shocks.

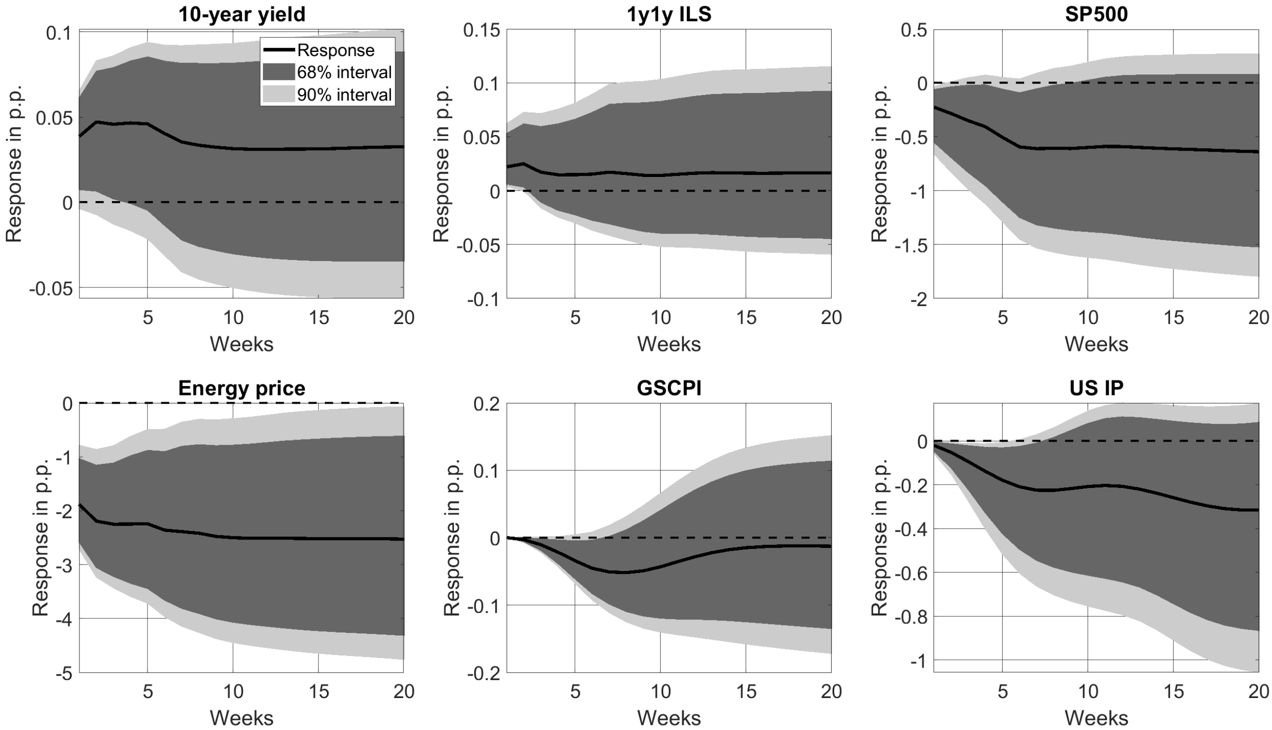

Figure 4: Impulse responses to domestic supply shock.

Notes: the figure reports the median (black solid line) response to a one standard deviation contractionary supply shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals.

long term. As expected, the shock has its greatest impact on industrial production, triggering a significant decline in energy prices of around 3% over the long term. The shock gradually spills over to the GSCP Index, while ILS rates decline and 10-year yields fall as well, consistent with a broader economic slowdown. A monetary policy shock increases 10-year yields by about 5 basis points for a one standard deviation shock. It also leads to declines in ILS rates, stock prices, and industrial production, though the effect on production becomes economically significant—around 0.5%—only after about one month. Supply chain pressures, however, remain broadly unaffected.

3.2 Post-Covid drivers of inflation expectations

To highlight the ability of the model to analyze the drivers of ILS rates at higher frequencies, we apply it to the case of the Covid-19 pandemic, which featured both sharp downward and upward shifts in ILS rates in the US. Figure 5 shows these dynamics were driven by a complex interaction of multiple shocks. Initially, the sharp drop in ILS rates after the onset of the pandemic was primarily caused by weaker demand as the outlook for economic activity contracted sharply in response to lockdowns (shown in the green

Table 4: Forecast error variance decomposition

	Macro shock	Monetary policy shock	Energy price shock	GVC supply shock	Other supply shock	Unexp.
			4-weeks horizon			
10-year yield	34.96	18.42	7.57	4.20	22.91	11.96
1Y1Y ILS	37.97	15.91	22.46	5.67	7.50	10.50
S&P 500	10.98	16.88	8.44	8.44	5.34	49.93
Energy price	29.45	12.78	5.06	0.24	36.38	16.08
GSCP Index	0.30	0.46	15.95	74.05	0.44	8.80
US IP	21.28	14.29	23.76	3.08	9.06	28.53
			12-weeks horizon			
10-year yield	33.7	18.1	8.0	4.6	22.6	13.0
1Y1Y ILS	37.3	15.9	22.3	6.1	7.6	10.8
S&P 500	11.5	16.8	8.7	8.4	6.3	48.3
Energy price	29.5	12.8	5.6	1.1	35.2	15.8
GSCP Index	2.4	1.7	12.7	72.3	1.5	9.5
US IP	26.8	12.4	21.1	6.1	9.1	24.5

Notes: forecast error variance decomposition at 4 weeks (1 month) the 12 weeks (1 quarter) horizon.

area). This drop was however rapidly reversed due to three factors. First, the pandemic lead to an unprecedented tightening of global supply chains—reflecting production shutdowns, labour shortages and transport bottlenecks—which caused upward price pressures as output adjustments were constrained (red area). Second, the accommodative policies of the Fed taken to offset the drop in demand contributed to supporting inflation expectations, when it cut its policy rate to zero while launching quantitative easing (blue area). Finally, OPEC+'s decision to significantly cut global oil production in the spring of 2020 further offset the downfall in inflation expectations as captured by the energy shock (yellow area). In early 2021, as vaccines were rolled out and the global economy reopened from the lockdowns, demand started to pick up strongly again. This was met with increasing global supply chain disruptions due to port congestions, surging shipping prices and labour mismatches, which pushed up inflation expectations steadily. In early 2022, Russia invaded Ukraine which worsened upward pressures on inflation amid the energy crisis it triggered, particularly in the euro area. This combination of shocks caused global inflation to surge, pushing US CPI inflation to a historic peak of over 9% in mid-2022. Shortly before inflation reached its peak, the Fed pivoted by aggressively raising interest rates by over 5% within 17 months, which swiftly lowered inflation expectations.

Yet as the model demonstrates, persistent upward demand pressures kept inflation expectations elevated together with domestic supply pressures—likely reflecting sustained labour market tightness (dark green)—kept inflation expectations elevated, counteracting the downward impact of monetary policy tightening and improving global supply chain conditions. In line with Giannone and Primiceri (2024) and Bernanke and Blanchard (2023), we find that macro shocks have been the main drivers of US inflation expectations in 2023-2024, marking a shift in underlying economic conditions from supply-driven to demand-driven shocks in ILS rates in the US.

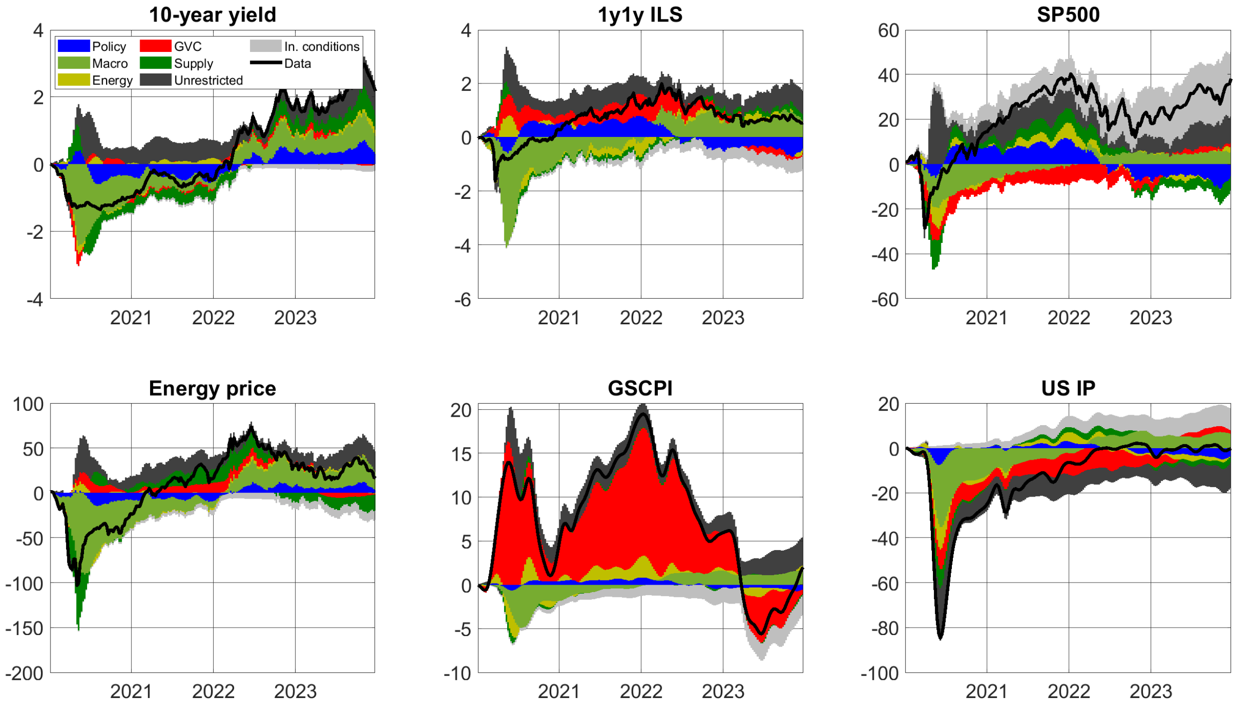

Figure 5: Historical decomposition between January 2020 and March 2024.
Notes: the figure reports the median historical decomposition for the period between January 2020 and March 2024. The black line reports the cummulated percentage changes of each variable, standardized to zero at the first observation.

Turning to other variables, the model attributes the significant movements in 10-year yields during that period primarily to the observed shifts in monetary policy and domestic macroeconomic shocks. Domestic supply shocks have played a role as well, particularly in the most recent period. Unsurprisingly, the steep declines in industrial production and stock prices were primarily driven by the collapse in domestic demand, while supply bottlenecks further exacerbated the economic impact of the pandemic on both variables. These negative pressures started to fade once the economy re-opened. As with ILS rates, monetary policy initially offset the negative effects of domestic demand weakness and supply constraints on both industrial production and the S&P 500 in the years following the pandemic. However, its contribution turned negative as policy began to normalize in 2022. The GSCP Index, as expected, is primarily driven by global value chain shocks. During the pandemic, energy prices were mostly steered by the large shifts in US demand, while also tighter supply chains conditions pushed them up throughout 2021 and 2022, in line with evidence from the impulse responses.

The forecast error variance decomposition, as shown in Table 4, highlights that for ILS rates, demand shocks—macro and monetary policy shocks—explain more than 50% of the variability at a 4-week ahead horizon, while supply shocks account for around one-third. Macro shocks emerge as the dominant driver, which is unsurprising given their broad scope in capturing diverse economic developments. This is the case for most variables in the model; macro shocks are also the primary drivers of forecast errors for yields, energy prices, and US industrial production, accounting for between 21% and 35% of the forecast error variance. Energy price shocks also play a significant role, explaining more than 20% of the forecast error variance in both market-based inflation expectations and US industrial production over the full sample. Monetary policy shocks emerge as the third most significant driver, explaining between 12% and 18% of the forecast error variance across all variables, excluding the supply chain index. The GSCP Index is almost entirely explained by GVC shocks, which account for about 70% of its variance. The unexplained component is largest for the S&P 500, which exhibits a strong trend, and for industrial production, which is affected by factors that are not easily captured at high frequency. As shown on Table 4, the results are comparable for forecast errors at a longer 12-week-ahead horizon.

3.3 Robustness

The results of the model remain robust across various changes to its specification. First, the findings are similar when using the 2-year instead of the 10-year yield as proxy for the US monetary policy stance, as shown in Appendix C.1. Second, incorporating the USD nominal effective exchange rate as an additional endogenous variable—and identifying a "global risk shock" capturing shifts in global risk sentiment that cause investors to move from risky equities to safer bonds, thereby leading to an appreciation of the US dollar in the spirit of Brandt et al. (2026)—does not significantly alter the results, as shown in

Appendix C.2. Finally, the results are also robust to excluding observations after 2019 from the estimation sample to avoid potential bias from the Covid-19 pandemic and subsequent recovery. In this case, we do not apply the Lenza and Primiceri (2022) correction and use the estimated model to filter shocks up to 2025, as shown in Appendix C.3.

Figure B.6 summarizes these tests by comparing the shocks estimated from the baseline model with those from the alternative specifications. It highlights that the correlation between the shocks from the baseline model and those from the robustness checks is high, underscoring the robustness of the results to these modifications. Interestingly, the only notable exception arises when the model includes only high-frequency variables, omitting the mixed-frequency dimension as detailed in Appendix C.4. In this case, the GVC shocks, in particular, differ substantially from those in the baseline model. This suggests that incorporating low-frequency restrictions indeed adds value in identifying the shocks of interest.

4 Transmission of weekly shocks to US inflation

This section investigates how the high-frequency shocks identified by Equation (2) pass through to monthly, aggregate prices. The results serve both as a validation of the model and as evidence of the added value that higher-frequency financial market data provide in offering timely signals to help policymakers better understand inflation dynamics. We also analyze the transmission of different types of supply shocks along the pricing chain to better understand their distinct economic effects—up to industry level. To do so, we rely on local projections à la Jordà (2005), and using a two-step procedure. In the first stage, we estimate the shocks using the mixed-frequency VAR model as outlined above; in the second stage, we project the effects of these shocks on selected economic variables to study their transmission. This approach follows similar methodologies used in Adolfsen et al. (2024), Dedola et al. (2017), Iacoviello and Navarro (2019), and Debortoli et al. (2023).

The following local projection equation is estimated:

$$y_{t+h} = \alpha_h + \beta_h s_t + \delta_h s(i)_t \cdot D + D + \Gamma_h X_t + \epsilon_{t+h} \tag{3}$$

y is the outcome variable, X is a vector of control variables, and s is a draw (i) of the identified structural shock.[15] The control variables include three lags of y, the US industrial production index, the WTI oil price, the 2-year government bond yield, the GSCP Index, and the nominal effective exchange rate.[16] D is a dummy variable equal to one for the months from March 2020 to December 2020. The dummy is used to capture the exceptional volatility of macroeconomic variables during the Covid-19 pandemic, which could affect the estimation of impulse responses in empirical samples. This is an adaptation to the local projection framework of Lenza and Primiceri (2022), who suggest down-weighting observations during the pandemic. Instead of down-weighting these observations, we extract from the estimate of δ the average response during the pandemic period. As shown in Figure B.7 to Figure B.9 in the Appendix, the large contractions in observed variables during the Covid-19 pandemic are indeed associated with sizeable identified shocks. All variables enter Equation (3) in logs with the exception of the GSCP Index, D, and the shocks. Because the shocks series s is a generated variable, standard errors are biased by construction as they do not account for uncertainty in the distribution of s. Hence, we construct confidence intervals as in Swanson (2021), based on 1,000 random draws from the posterior distribution of the structural shocks. The coefficient β_t from Equation (3) for $h = 1, \ldots, H$ gives the response of y at time $t + h$ to one standard deviation of the shock at time t. Responses are standardized to a one-standard deviation of each shock.

We estimate Equation (3) on the full sample and on a restricted sample ending in December 2019 to highlight how the exceptional period of post-Covid inflation deviated from historical regularities. Figure 6 presents the impulse responses from Equation (3), where the dependent variables are headline, core, and energy CPI. Figure 7 displays the responses of import prices, producer prices, and services prices, while Figure 8 provides a more detailed view by showing the responses of producer prices at the industry level. For brevity, we focus on discussing the transmission following the three types of supply-side shocks.

[15] Shocks occurring within the same month are aggregated by summing them, thereby converting the data from weekly to monthly frequency.

[16] As the variable of interest (s) is a structural shock, it is by construction orthogonal to macro variable contemporaneously. However, local projections suffer for larger confidence intervals than VARs, therefore controlling for additional drivers of the dependent variables helps in reducing the residuals of the regression and the uncertainty of the estimator. For this reason we include as controls a measure of activity, oil prices, yields and supply bottlenecks all of which contribute in explaining the volatility of price aggregates. Jordà (2005) additionally shows analytically how lags of the endogenous variables appear in the local projection representation of the VAR.

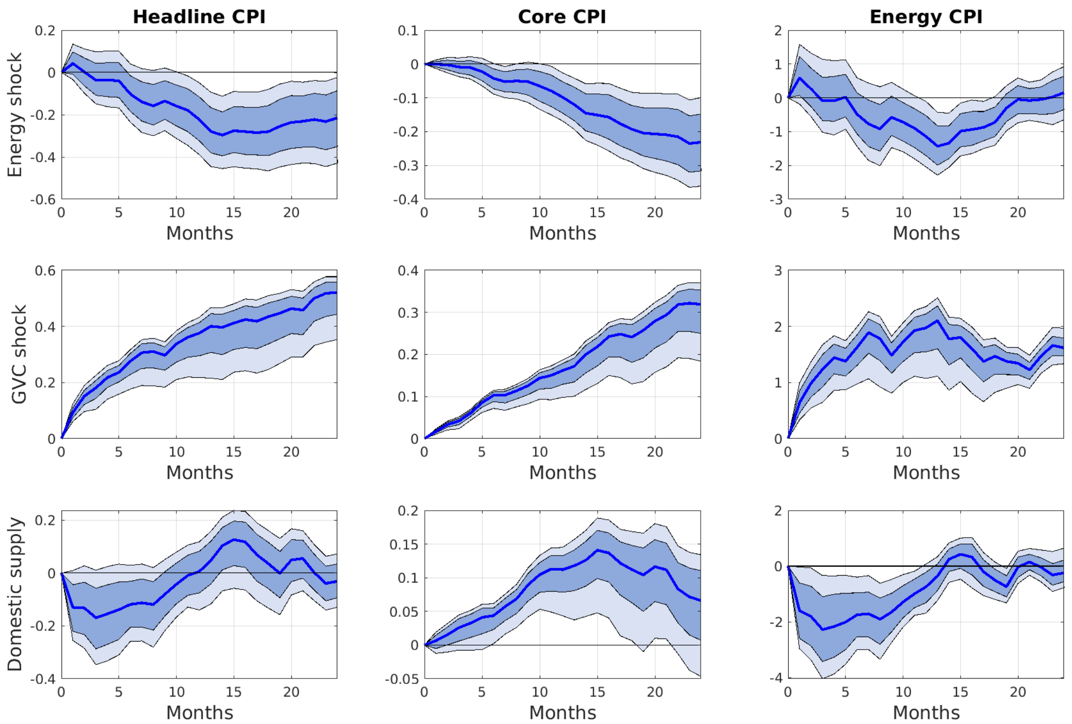

Figure 6: Impulse responses of headline, core and energy CPI

Notes: the figure reports the impulse responses to energy supply, global value chain (GVC) and domestic supply shocks computed as in Equation (3). The shaded areas denote the 68% and 95% confidence intervals.

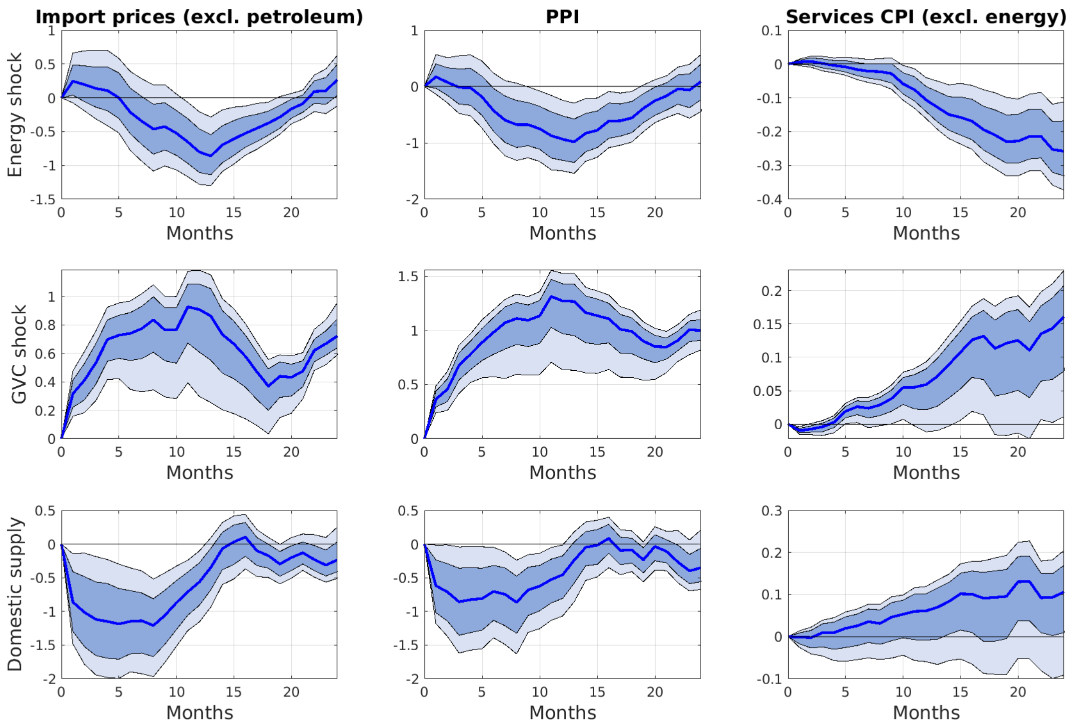

Figure 7: Impulse responses of selected price indices.

Notes: the figure reports the impulse responses to the energy supply, global value chain (GVC) and domestic supply shocks computed as in Equation (3). The shaded areas denote the 68% and 95% confidence intervals.

Two key findings stand out. The first is that the responses of US inflation differ substantially across the three types of supply shocks, as already indicated by the impulse responses from the mixed-frequency VAR (see Figure 2-4). Following energy supply shocks, the inflationary effects are typically short-lived: the initial energy price surge lifts headline CPI through the energy component, but the effect quickly reverses as higher energy prices weigh on economic activity. That contraction in turn pulls the energy price down, which returns to its initial level after around five months. Core consumer prices (excluding energy) remain stable for about one quarter, as higher energy prices are not transmitted further, but then decline as increased energy costs weigh on economic activity. As shown in Figure 7, the response of import prices, producer prices and services are also—with some delay—dominated by the contractionary impact of the energy supply shock.

Interestingly, when examining the effect of the energy supply shock on producer prices at the industry level, as shown in Figure 8, it becomes evident how localized the inflationary impact is. The median maximum response to the energy shock (indicated in red) is highest in industries such as metal manufacturing, petroleum and coal production, electric power generation, and oil and gas extraction—sectors that are either directly tied to energy prices or are highly energy-intensive. As for services prices, inflationary effects are most pronounced in specific sectors such as travel agencies and services related to car rentals and leasing, as illustrated in Figure 8. In contrast, most other industries do not raise their producer prices. Instead, reflecting the contractionary nature of the energy supply shock on demand, producer prices in most sectors decline with some delay, as indicated by the negative values of the median minimum response over the estimation horizon (shown in blue).

Global value chain (GVC) shocks, by comparison, have a much more persistent and broad-based impact on price aggregates. Both headline and core inflation remain elevated—by approximately 0.6% and 0.4%, respectively—even two years after the initial shock. This persistence stems from two main factors. First, GVC shocks raise import prices, even when oil is excluded. This aligns with the primary transmission channel of value chain disruptions: reduced availability of critical imported inputs that constrain domestic production across multiple sectors, requiring prices to adjust—sometimes sharply—to clear the market. Second, and consistent with the impulse responses from the mixed-frequency VAR, CPI energy prices also increase. This suggests that such disruptions also elevate marginal costs in the energy sector, pushing energy prices higher despite a contracting economy. As discussed earlier, this dynamic undermines a typical automatic stabilizer—falling energy prices during economic downturns—which usually helps to dampen cost pressures. Instead, higher energy prices spill over into the broader economy following the GVC shock, raising costs for domestically produced goods and triggering further increases in prices and wages beyond those inflicted by higher non-energy import prices. Indeed, producer prices and the prices of services show sustained increases, as illustrated in Figure 7.

Industry-specific responses also reveal the broad-based nature of the increase in producer prices following the GVC shock, as illustrated in Figure 8. The maximum response is significant across nearly all manufacturing industries, which stands in stark contrast to the more localized effects observed in response to the energy supply shock. Similarly, service industries also experience widespread and significant price increases. Although the GVC shock exerts downward pressure on growth, these contractionary forces are not sufficient to offset its inflationary effects. This is reflected in the median minimum responses over the estimation horizon, which remain close to zero rather than turning negative (as shown in blue).

Together, these results highlight the persistent nature of GVC shocks, as they tend to amplify price pressures across the board, producing compounding effects. This key result aligns with recent theoretical models showing that binding supply constraints reduce production capacity and raise prices, leading to persistent inflation, see Comin et al. (2023). It also supports empirical findings of strong, lasting effects from global value chain shocks in the US and euro area, see De Santis (2024) and Ascari et al. (2024).

Finally, the effect of domestic supply shocks on headline inflation are muted in comparison to the other two supply shocks. However, this hides a strong effect on core CPI that takes several months to unfold. Figure 7 reveals that these upwards pressures are mostly driven by a rise in services inflation. This supports the interpretation that such supply shocks stem from domestic supply pressures such as the labour market pressures, where rising wages in a tight labour market push up services inflation, as also seen in the aftermath of the Covid-19 pandemic. Industry-level price responses in Figure 8 further

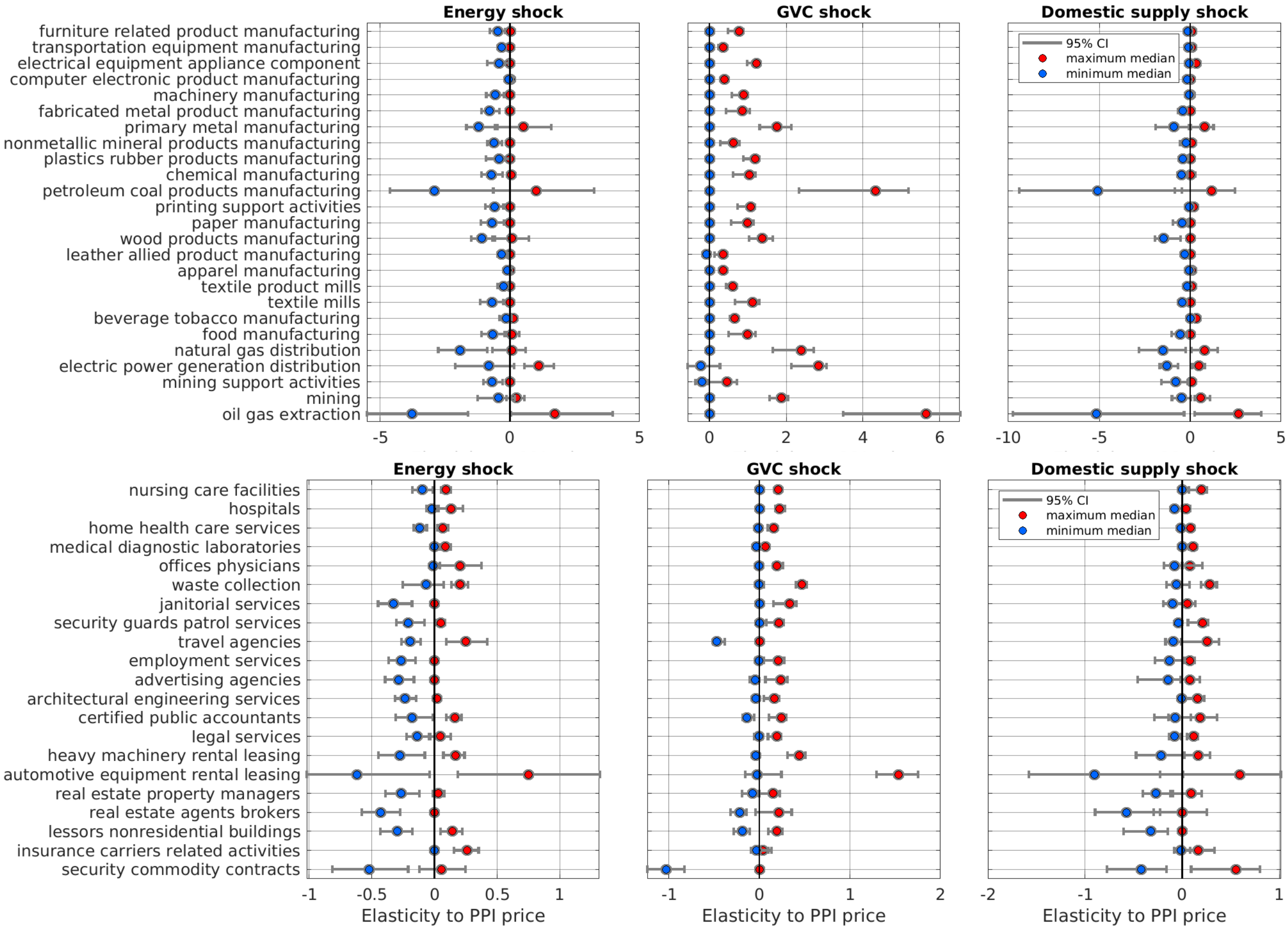

Figure 8: Elasticity of industry-specific PPI indices to supply shocks.

Notes: the figure reports the minimum and maximum response to supply shocks for industry-specific PPI prices. Impulse responses are estimated as in Equation (3) where the dependent variable is the industry-specific PPI. All industries listed in the US Bureau of Labor Statistics NAICS classification are considered. Bars report 95% confidence intervals; impulse responses are computed over a 24 periods horizon (2 years).

reinforce this view, showing that most of the inflationary response is concentrated in service industries rather than manufacturing. Compared to the broad-based impact of the GVC shock, the effect of domestic supply shocks is notably more contained. And similar to energy supply shocks, the upward pressure on core inflation through services following the domestic supply shock is partially offset by its contractionary nature, which results in declines in import prices, energy prices, and producer prices across industries with some delay.

These inflationary patters following the different types of supply shocks reveal a few key insights. First, the traditional wisdom of "looking through" supply shocks, as proposed by Blanchard and Gali (2007), indeed appears to apply when the supply shock originates in the energy market. In this case, the contractionary impact of an energy price shock is sufficient to ease inflationary pressures over the medium term. Domestic supply shocks are similarly manageable and typically require less aggressive policy responses, according to our results. In fact, there are endogenous stabilizers—such as energy prices—that help offset the inflationary effects of these domestic shocks. However, monetary policy makers face greater challenges when inflation arises from global value chain disruptions, which tend to exert more persistent pressure on prices. Because such pressures are broad-based, stabilizing channels—like declining energy prices—are less effective. As a result, central banks face a sharper trade-off between price stability and output stabilization.

The stark differences in the inflationary effects of various supply shocks highlight the importance of timely identification of their underlying sources for effective policy responses. The second key implication of the results is that our mixed-frequency model is able to do that; the high-frequency model provides valuable quasi real-time insights into the key drivers of inflation dynamics—even before conventional data becomes available. Given that the appropriate monetary policy response can vary significantly depending on the nature of the shock, this model serves as a useful tool for supporting timely and effective policy decisions.

4.1 Responses excluding the Covid-19 period

Given that the Covid-19 shock led to an unprecedented surge in US inflation—driven by both large demand and supply disturbances that can bias average estimated coefficients—we examine the robustness of our results to the exclusion of the post-pandemic period. Figures Figure B.10 and Figure B.11 in the Appendix compare the estimated inflation dynamics following the supply shocks using two samples: the full sample (blue line) and a restricted sample ending in December 2019 (red line), which excludes the post-Covid period. In this restricted sample, variable D and its interaction terms are omitted from the set of control variables in Equation (3).

Overall, the results indicate that the inflationary dynamics following the three types of supply shocks remain robust and statistically significant, although-—as expected-—their magnitude is somewhat reduced in the restricted sample. The most notable differences arise in response to the GVC shock. While the qualitative pattern remains similar, the quantitative impact is markedly smaller: the peak inflation response in the pre-pandemic sample is roughly half that observed in the full sample. This reduction is primarily driven by a more muted reaction in core inflation—about 0.05 percentage points in the restricted sample compared to 0.3 percentage points in the full sample—as well as a less pronounced increase in energy consumer prices. Moreover, in the restricted sample, core prices fully absorb the impact of GVC shocks within approximately two years, stabilizing more quickly than when including the post-pandemic period. Significant but more muted responses are also observed for the other price aggregates, as shown in Figure B.11. These findings underscore the unique nature of GVC shocks following the global pandemic, which were stronger, more persistent, and more broadly transmitted to inflation than in historical episodes. In comparison, the estimated inflationary effects show less differences in magnitude for the energy and domestic supply shocks.

Overall, the results from the restricted sample emphasize the distinctiveness of the Covid-19 period in recent economic history. The sequence and scale of shocks were unprecedented, likely inducing non-linear responses in aggregate prices, with price reactions, on average, being more than twice as strong as those observed in the pre-pandemic sample. This finding supports the view that the 2022–23 inflation spike was driven by a combination of shocks that triggered disproportionately larger responses than historical price elasticities would predict for shocks of similar magnitude—thereby making it more challenging for policymakers to timely identify the inflationary impact and persistence.

5 Conclusion

In the aftermath of the Covid-19 pandemic, inflation in the United States surged to its highest levels in decades, driven primarily by supply shocks stemming from global supply chain disruptions, labour shortages, and energy market volatility. For policymakers, swiftly pinpointing the underlying drivers of these inflationary pressures became essential to prevent policy errors that might worsen inflation or jeopardize the economic recovery. This paper investigates the impact of supply shocks during this period and presents a new higher-frequency framework designed to identify the structural forces behind US inflation, utilizing inflation-linked swap (ILS) rates as a market-based indicator.

Our proposed framework employs a mixed-frequency approach, combining high-frequency financial market data with lower-frequency economic indicators, to identify five key structural drivers of ILS rates: aggregate demand, monetary policy, global value chain (GVC) shocks, energy supply shocks, and domestic supply shocks. The results reveal striking differences in how these various supply shocks affect inflation, with important implications for policy design.

Energy supply shocks, for instance, tend to have narrow and short-lived impacts on inflation. Their effects are largely confined to headline consumer prices, with limited pass-through to core inflation. Their inflationary impact is often offset by a dampening effect on economic growth, as higher energy costs reduce overall demand. In contrast, domestic supply shocks, which are typically driven by labour market constraints, transmit more strongly to core inflation. However, this transmission is partially mitigated by the contractionary effects these shocks impose on economic activity, as rising costs curb economic output. GVC shocks, on the other hand, stand out as the most persistent and widespread drivers of inflation. Disruptions in global supply chains ripple across production processes, limiting the availability of essential inputs at all stages of production. This constrains output, sustains upward pressure on prices for extended periods, and delays the normalization of inflationary pressures. These findings carry significant policy implications. While central banks can often "look through" energy supply shocks due to their transitory nature, domestic and GVC shocks require more nuanced and proactive responses. GVC disruptions, in particular, heighten the trade-off between stabilizing output and controlling inflation, often necessitating more aggressive monetary policy interventions. Policymakers face the challenge of balancing these competing priorities, especially when inflationary pressures are deeply rooted in supply-side disruptions.

The framework introduced in this paper provides a timely and precise identification of inflation drivers at a weekly frequency, offering policymakers valuable quasi real-time insights. When applied to the Covid-19 period, the model effectively captures the evolving dynamics of inflation expectations, highlighting the complex interplay between shifting demand pressures and supply-side constraints driven by GVC bottlenecks, energy supply disruptions, and domestic labour market constraints. Monetary policy played a crucial role throughout this period. Initially, it counteracted the sharp decline in inflation expectations caused by the dramatic collapse in demand following the Covid-19 outbreak. Later, as the US economy reopened, the aggressive response of the Federal Reserve helped temper the steep rise in inflation that emerged when surging demand collided with persistent supply-side disruptions from GVC bottlenecks and domestic supply constraints.

While the abrupt shift in inflation dynamics and the persistence of record-high inflation that followed posed significant challenges for policymakers to anticipate, our framework helps shedding light on demand- and supply-side drivers of inflation expectations at higher frequencies. By doing so, it offers valuable insights into the mechanics of inflation dynamics and their implications for more effective and responsive monetary policymaking.

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Appendix

A Tables

Table A.1: Estimation of Equation (1) using financial variables

	US Vix						
	$L=0$	$L=1$	$L=2$	$L=3$	$L=4$	$L=5$	$L=6$
β_0	0.51	0.61	1.18	1.45	1.13	1.30	0.88
	(0.93)	(0.91)	(0.83)	(0.79)	(0.84)	(0.82)	(0.88)
β_1		0.54	0.65	1.22	1.46	1.18	1.32
		(0.92)	(0.91)	(0.83)	(0.79)	(0.83)	(0.81)
β_2			0.76	0.92	1.37	1.67	1.31
			(0.89)	(0.87)	(0.81)	(0.77)	(0.82)
β_3				0.67	0.79	1.32	1.58
				(0.90)	(0.89)	(0.82)	(0.78)
β_4					0.32	0.49	0.96
					(0.95)	(0.93)	(0.87)
β_5						0.66	0.79
						(0.91)	(0.89)
β_6							0.59
							(0.92)
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N	226	225	224	223	222	221	220
	US 10-year yield						
	$L=0$	$L=1$	$L=2$	$L=3$	$L=4$	$L=5$	$L=6$
β_0	-6.79	-4.99	-5.38	-5.47	-5.69	-5.69	-6.96
	(0.16)	(0.32)	(0.29)	(0.28)	(0.26)	(0.26)	(0.17)
β_1		-5.08	-3.06	-3.39	-3.39	-3.62	-3.23
		(0.31)	(0.56)	(0.52)	(0.52)	(0.49)	(0.54)
β_2			-5.51	-3.41	-3.79	-3.87	-4.28
			(0.27)	(0.52)	(0.47)	(0.47)	(0.42)
β_3				-5.71	-3.55	-3.73	-3.71
				(0.26)	(0.50)	(0.48)	(0.49)
β_4					-5.95	-3.94	-4.15
					(0.24)	(0.46)	(0.44)
β_5						-5.32	-3.18
						(0.30)	(0.55)
β_6							-5.80
							(0.26)
R^2	0.01	0.01	0.02	0.02	0.03	0.03	0.04
N	226	225	224	223	222	221	220
	S&P 500 index						
	$L=0$	$L=1$	$L=2$	$L=3$	$L=4$	$L=5$	$L=6$
β_0	-29.47	-25.14	-28.27	-27.25	-24.66	-23.68	-24.78
	(0.27)	(0.35)	(0.30)	(0.32)	(0.37)	(0.39)	(0.37)
β_1		-23.38	-18.02	-21.23	-21.09	-18.53	-17.16
		(0.39)	(0.52)	(0.45)	(0.45)	(0.51)	(0.54)
β_2			-25.67	-20.89	-23.48	-23.20	-20.29
			(0.35)	(0.45)	(0.40)	(0.41)	(0.47)
β_3				-22.77	-18.98	-21.61	-21.06
				(0.40)	(0.50)	(0.44)	(0.45)
β_4					-19.50	-15.56	-18.41
					(0.48)	(0.58)	(0.51)
β_5						-20.41	-15.56
						(0.46)	(0.58)
β_6							-24.58
							(0.38)
R^2	0.01	0.01	0.01	0.02	0.02	0.02	0.03
N	226	225	224	223	222	221	220

Notes: the table reports parameter estimates for Equation (1) when US financial variables (VIX index, the SP 500 index and the US 10-year yield) are used as controls instead of industrial production. P-values are reported in parenthesis below the coefficients along with the adjusted R^2. The VIX and the SP 500 enter the regression in log-changes, the US 10-year yield is used in first differences while the GSCP Index in simple changes.

B Figures

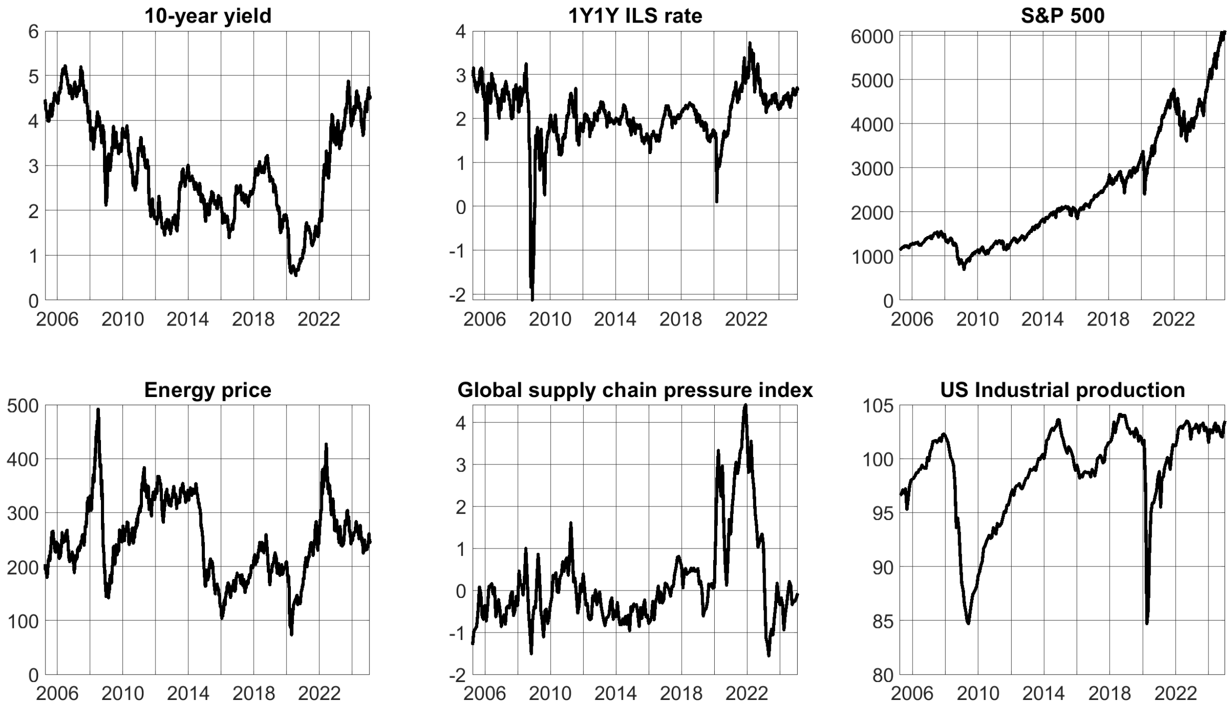

Figure B.1: Endogenous variables in the mixed-frequency VAR model.
Notes: all variables are at weekly frequency except for the Global Supply Chain Pressure Index and the US industrial production index that are available at monthly frequency.

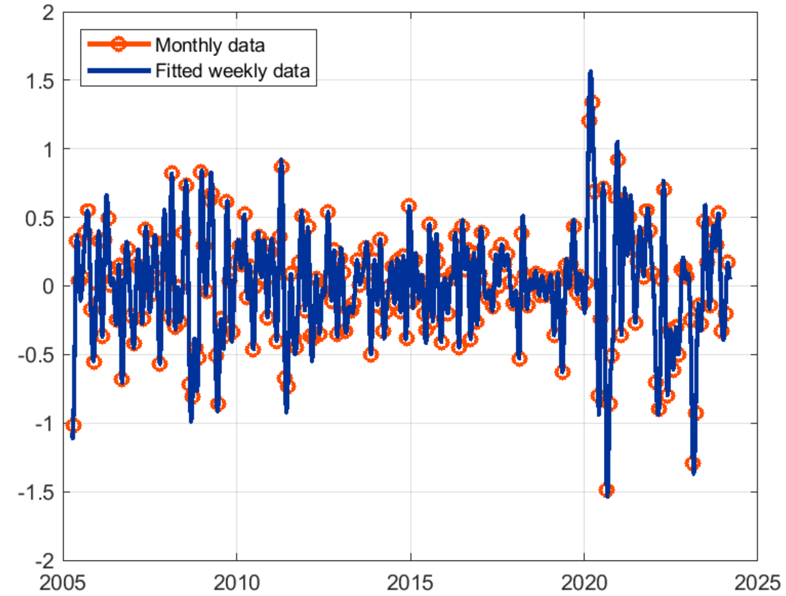

Figure B.2: Weekly filtered Global Supply Chain Pressure Index.
Notes: the figure shows the (median) weekly filtered evolution of the Global Supply Chain Pressure Index based on the monthly Federal Reserve Bank of New York index, see Abbai et al. (2022). Variables are reported in first differences.

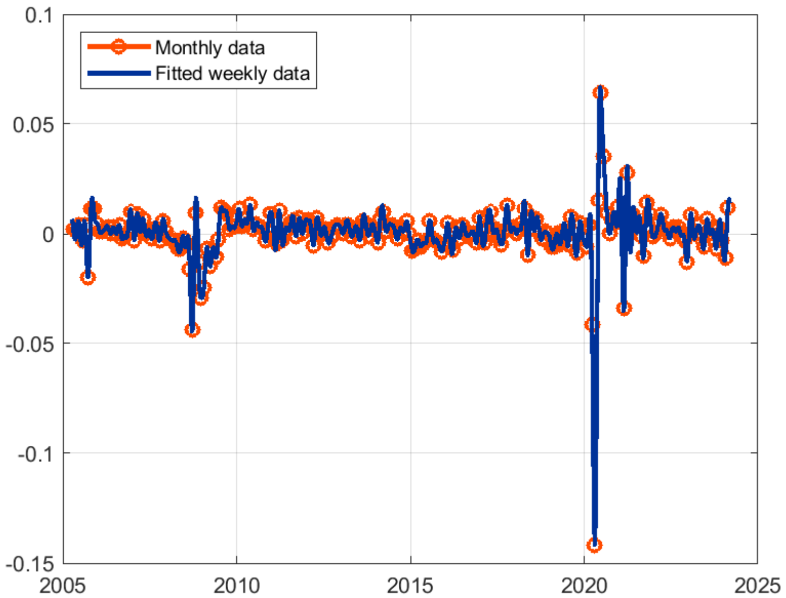

Figure B.3: Weekly filtered US industrial production.
Notes: the figure shows the (median) weekly filtered evolution of the US industrial production index. Variables are reported in first differences.

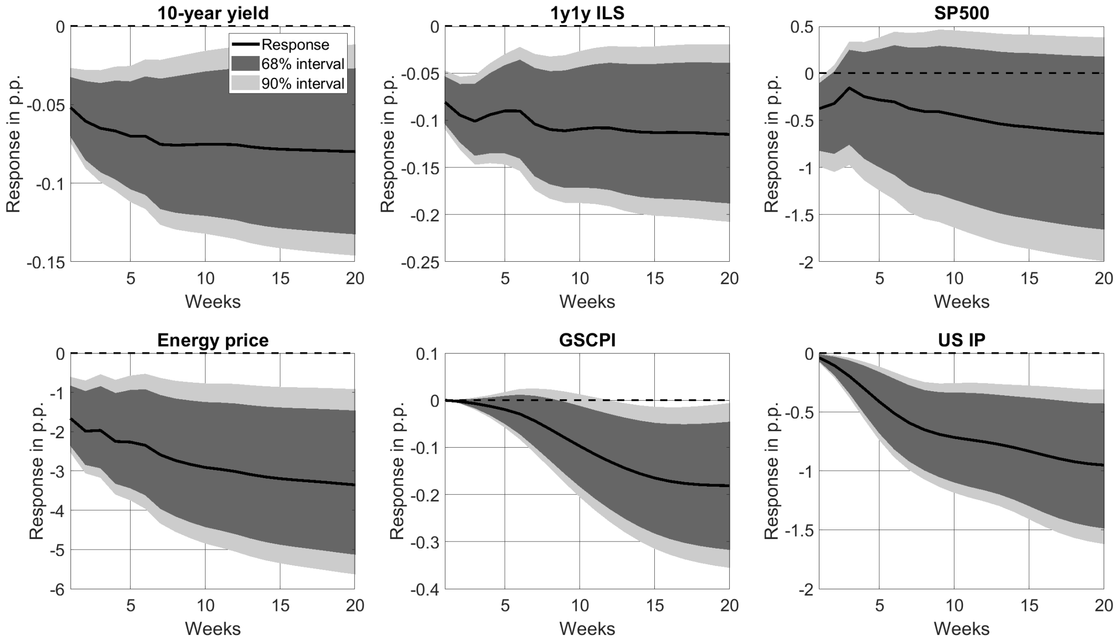

Figure B.4: Impulse responses to a macroeconomic demand shock.

Notes: the figure reports the median (black solid line) response to a one standard deviation contractionary macroeconomic shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals.

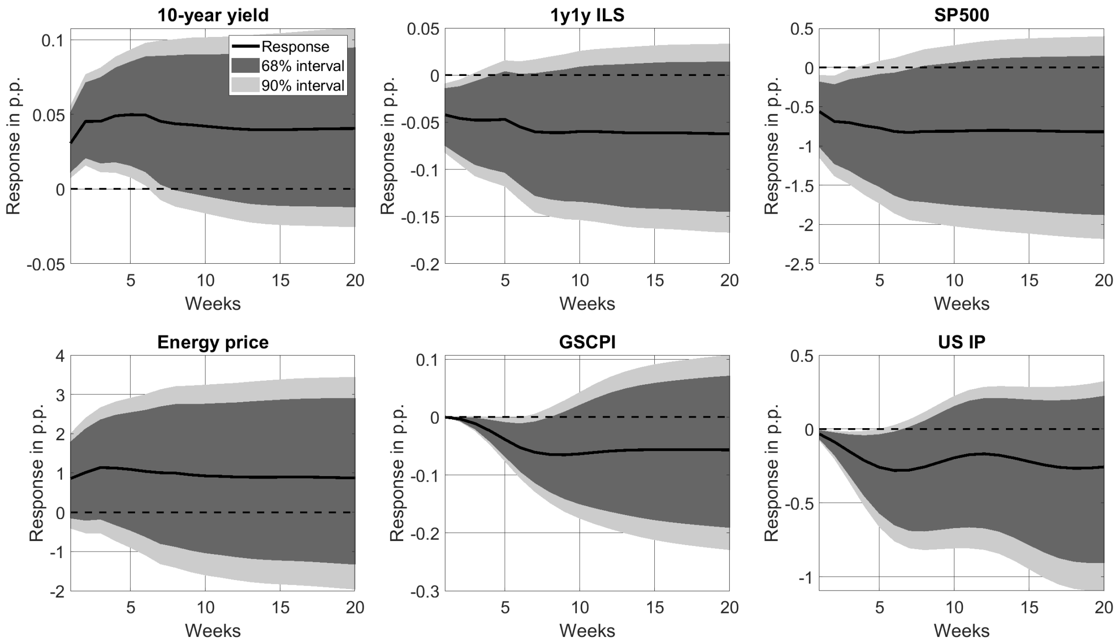

Figure B.5: Impulse responses to a monetary policy shock.

Notes: the figure reports the median (black solid line) response to a one standard deviation contractionary monetary policy shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals.

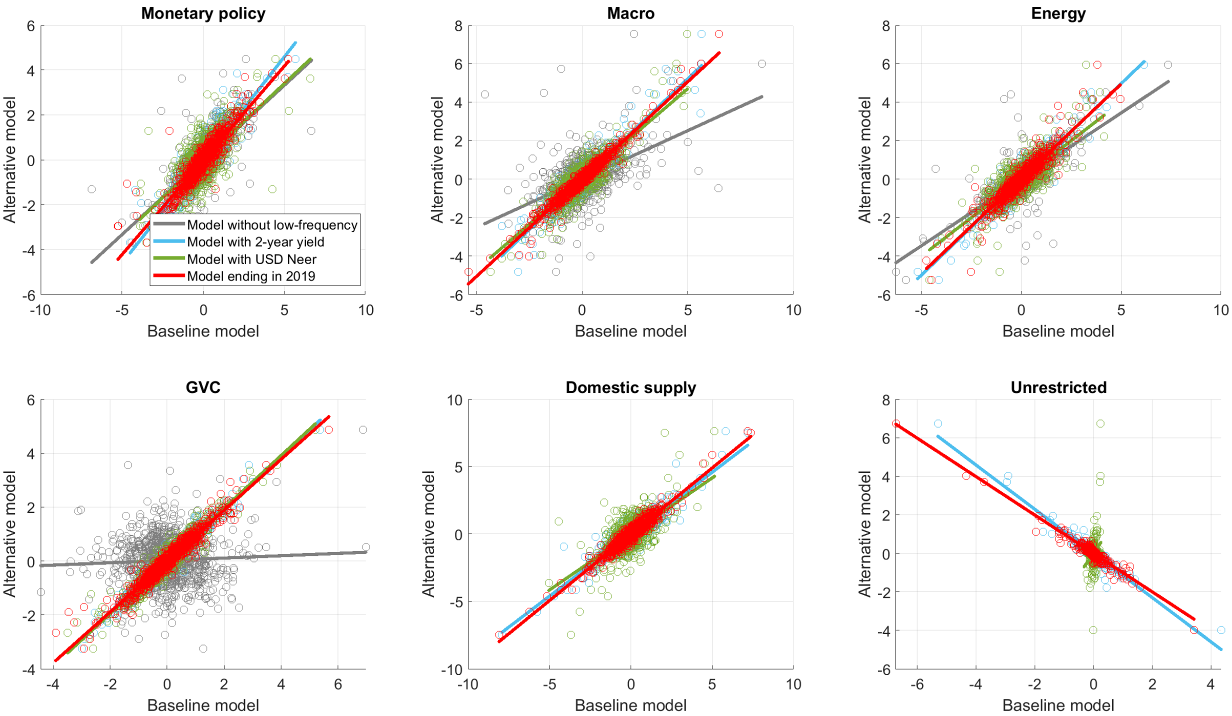

Figure B.6: Shock correlation across models.

Notes: the figure shows the correlation of structural shocks across models. The shocks from the baseline model are reported on the horizontal axis while shocks from the alternative specifications are on the vertical axis. Three alternative specifications of the model are considered: i) no low-frequency variables; ii) the 2-year yield substituting the 10-year yield as endogenous variable; iii) adding the US dollar nominal effective exchange rate as additional endogenous variable; iv) ending the sample in 2019.

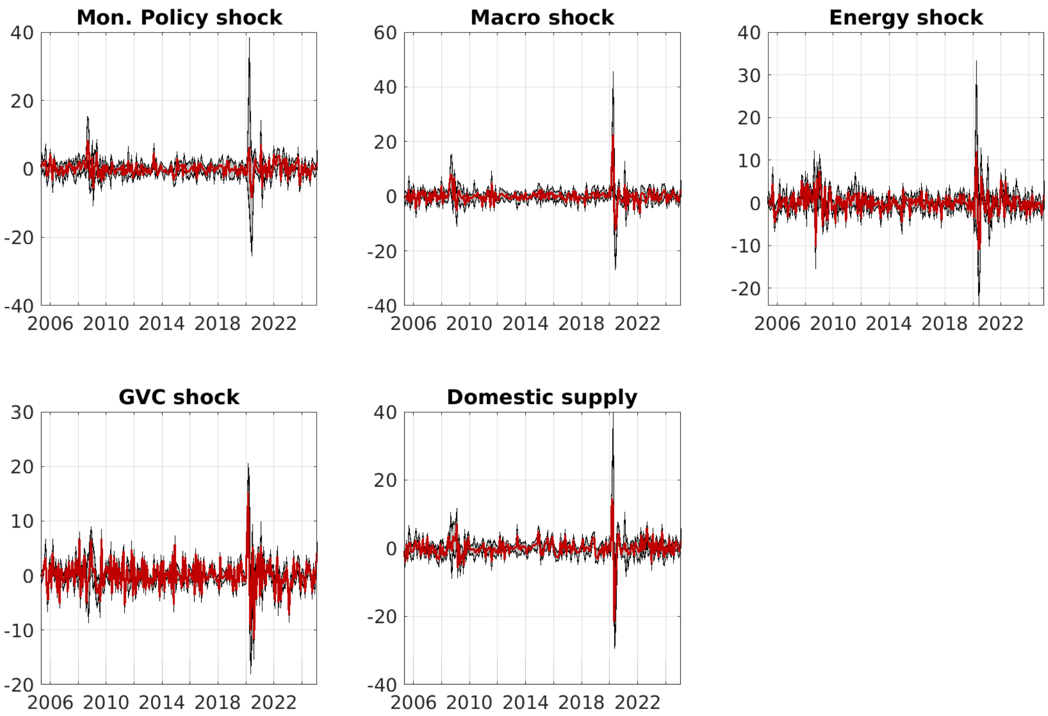

Figure B.7: Estimated shocks.

Notes: the figure depicts the estimated shocks from Equation (2) aggregated at a monthly frequency. The red solid line represents the median shock across 1,000 draws from the posterior distribution of the model. The shaded areas indicate the 68th and 90th percentiles of the shocks from the distribution.

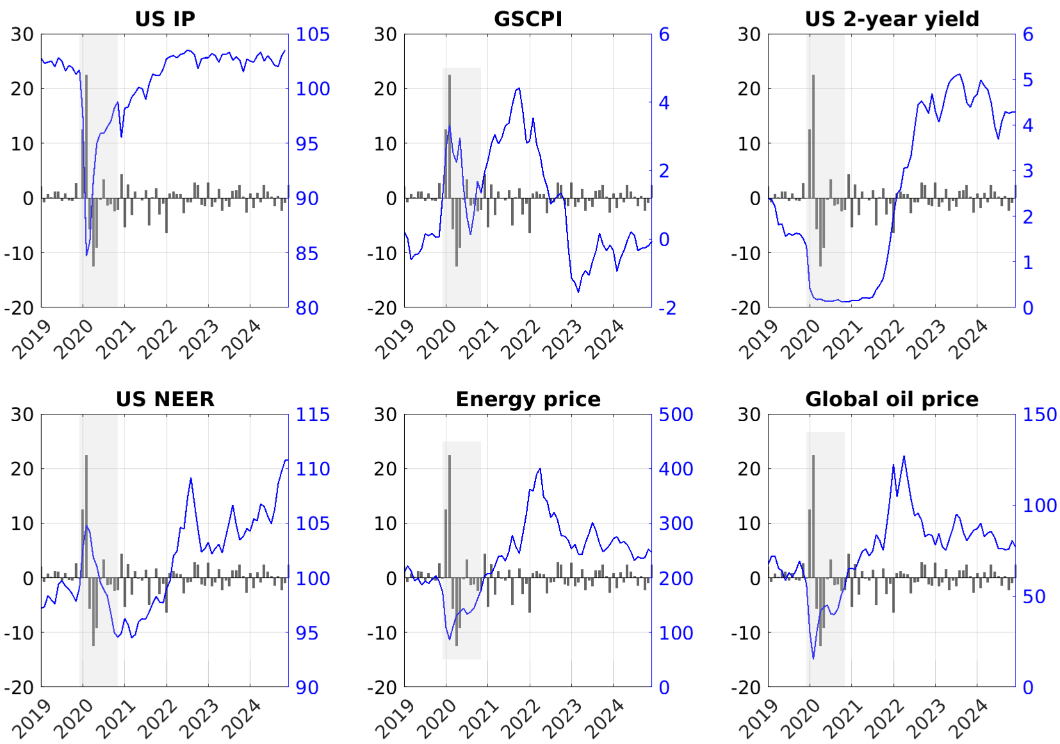

Figure B.8: Macroeconomic demand shocks during the Covid-19 outbreak.

Notes: the figure illustrates the estimated macroeconomic demand shock derived from Equation (2) alongside selected macroeconomic variables of interest. The grey shading highlights the period corresponding to the Covid-19 outbreak.

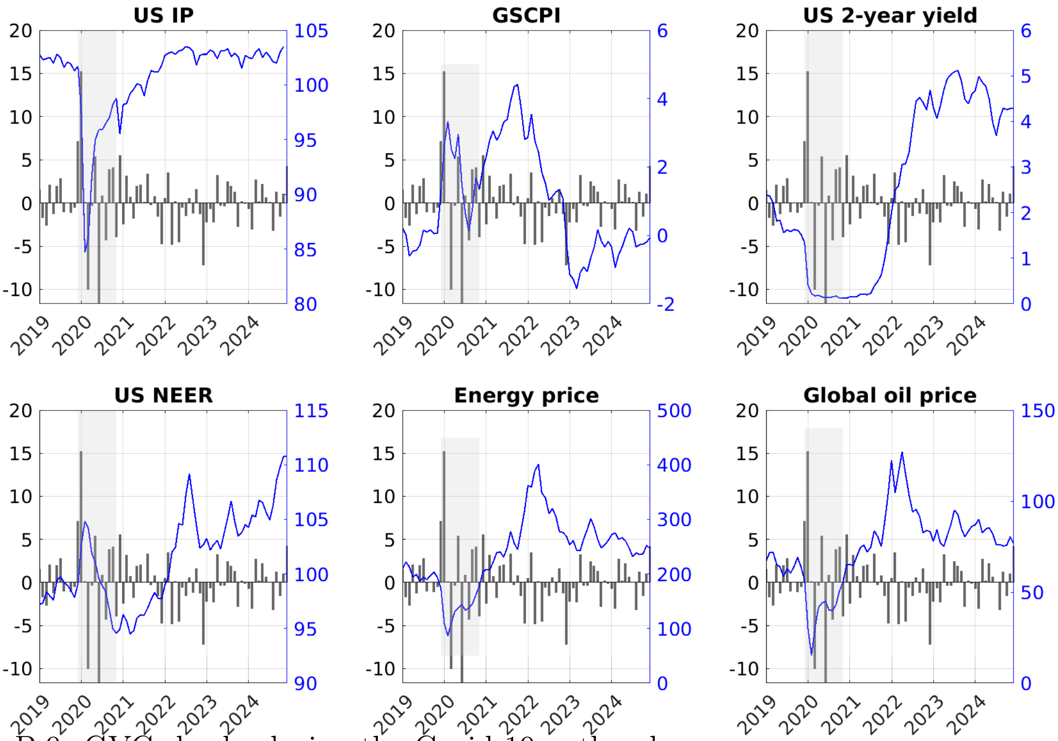

Figure B.9: GVC shocks during the Covid-19 outbreak.

Notes: the figure illustrates the estimated global value chain shock derived from Equation (2) alongside selected macroeconomic variables of interest. The grey shading highlights the period corresponding to the Covid-19 outbreak.

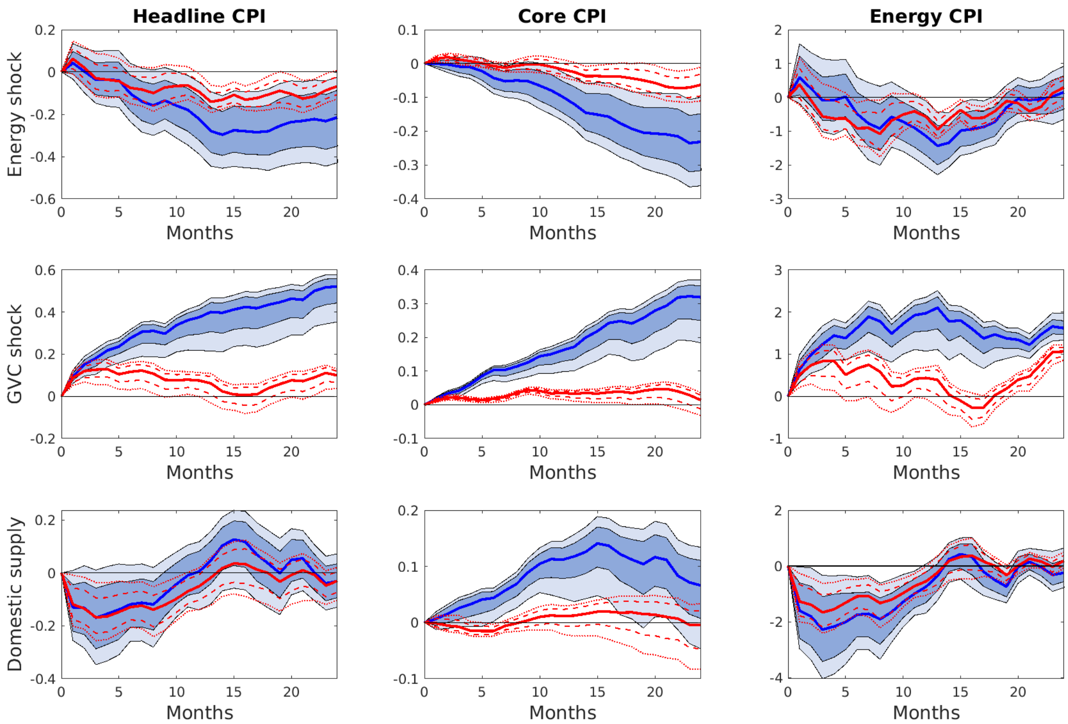

Figure B.10: Impulse responses of headline, core and energy CPI

Notes: the figure reports the impulse responses of headline, core CPI and energy CPI to energy supply, global value chain (GVC) and domestic supply shocks computed as in Equation (3). The results from the estimation over the entire period of analysis are presented in blue, while those based on data up to 2019 (pre-COVID period) are illustrated in red. The shaded areas and dashed lines denote the 68% and 95% confidence intervals.

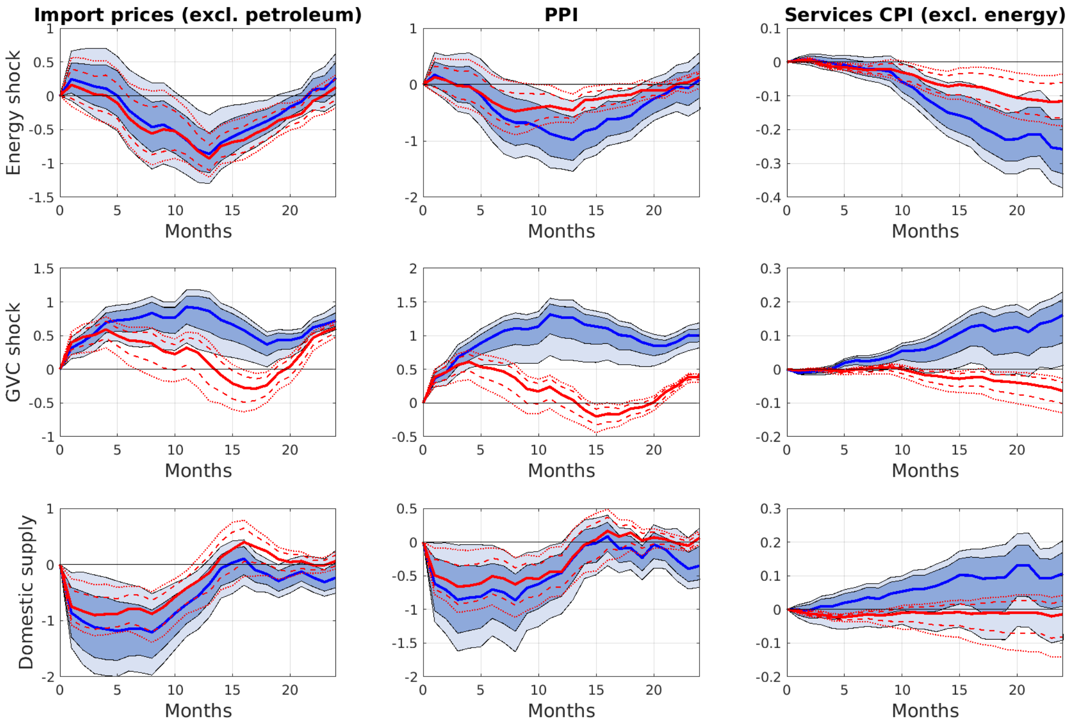

Figure B.11: Impulse responses of selected price indices

Notes: the figure reports the impulse responses of price indices to energy supply, global value chain (GVC) and domestic supply shocks computed as in Equation (3). The results from the estimation over the entire period of analysis are presented in blue, while those based on data up to 2019 (pre-COVID period) are illustrated in red. The shaded areas and dashed lines denote the 68% and 95% confidence intervals.

C Extensions & Robustness

C.1 Model estimated with the 2-year instead of 10-year yield

This section reports the main results when the US 2-year yield is used instead of the 10-year yield as proxy for US financial conditions and monetary policy. The identification scheme remains the same as in Section 3.

Table C.2: Forecast error variance decomposition – model with 2-year yield

	Macro shock	Monetary policy shock	Energy price shock	GVC supply shock	Domestic supply shock	Unres. shock
			4-weeks horizon			
2-year yield	35.70	17.81	3.82	4.66	25.85	12.16
1Y1Y ILS	30.76	19.25	28.84	7.71	5.34	8.11
S&P 500	14.69	16.11	3.26	8.71	4.25	52.99
Energy price	22.08	14.75	6.66	0.27	43.03	13.22
GSCPI Index	0.25	0.70	18.26	69.07	0.66	11.06
US IP	22.95	14.26	29.45	4.63	6.22	22.49
			12-weeks horizon			
2-year yield	35.9	17.6	3.9	4.8	25.5	12.2
1Y1Y ILS	30.5	19.0	28.2	8.0	5.6	8.6
S&P 500	15.1	16.2	3.7	8.6	5.2	51.2
Energy price	22.5	14.8	7.0	1.1	41.5	13.1
GSCPI Index	1.7	2.7	15.4	67.2	2.0	10.9
US IP	28.0	13.1	24.8	6.7	7.6	19.8

Notes: forecast error variance decomposition at 4 weeks (1 month) the 12 weeks (1 quarter) horizon. The US 10-year yield is substituted with the 2-year maturity. The identification scheme remains the same as in Section 3.

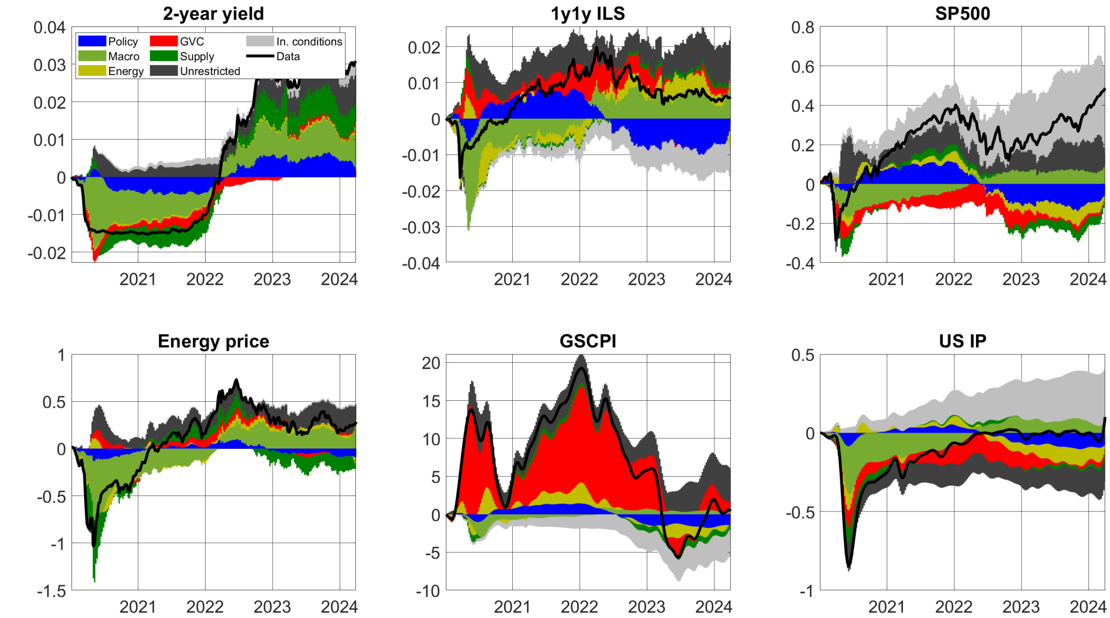

Figure C.12: Historical decomposition from January 2020 to March 2024 using the 2-year yield.

Notes: the figure reports the median historical decomposition for the period between January 2020 and March 2024. The black line reports the cummulated percentage changes of each variable, standardized to zero at the first observation. Contributions are computed using 1000 draws from the posterior of Equation (2). The 2-year instead of the 10-year yield is used.

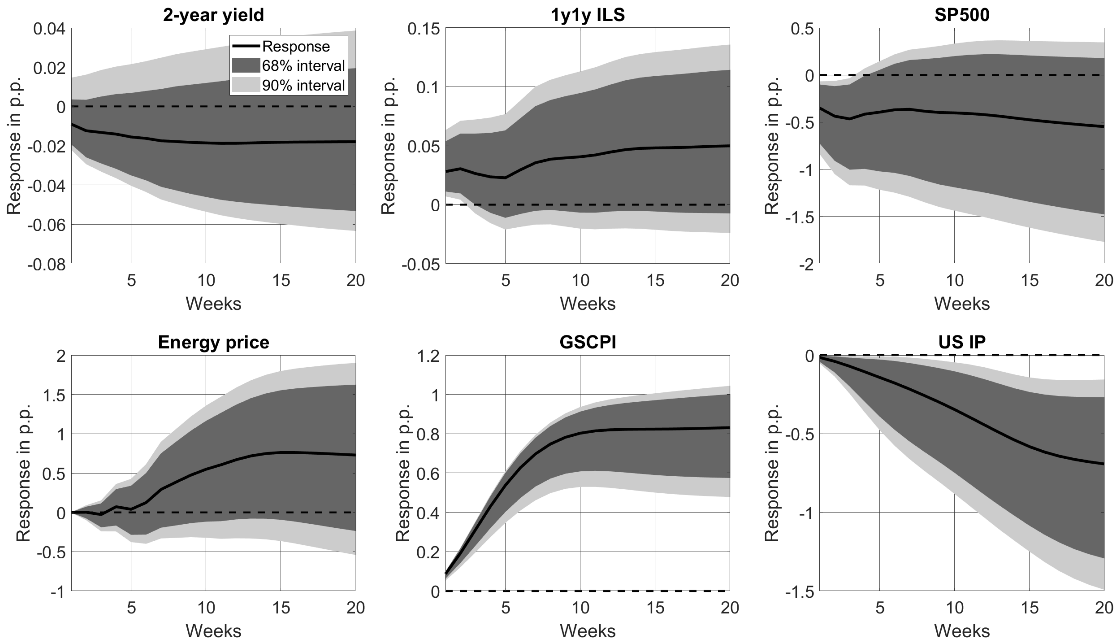

Figure C.13: Impulse responses to a global value chain shock using the 2-year yield.

Notes: the figure reports the median (black solid line) response to an contractionary supply shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals. Responses are computed using 1000 draws from the posterior of Equation (2). The 2-year instead of the 10-year yield is used.

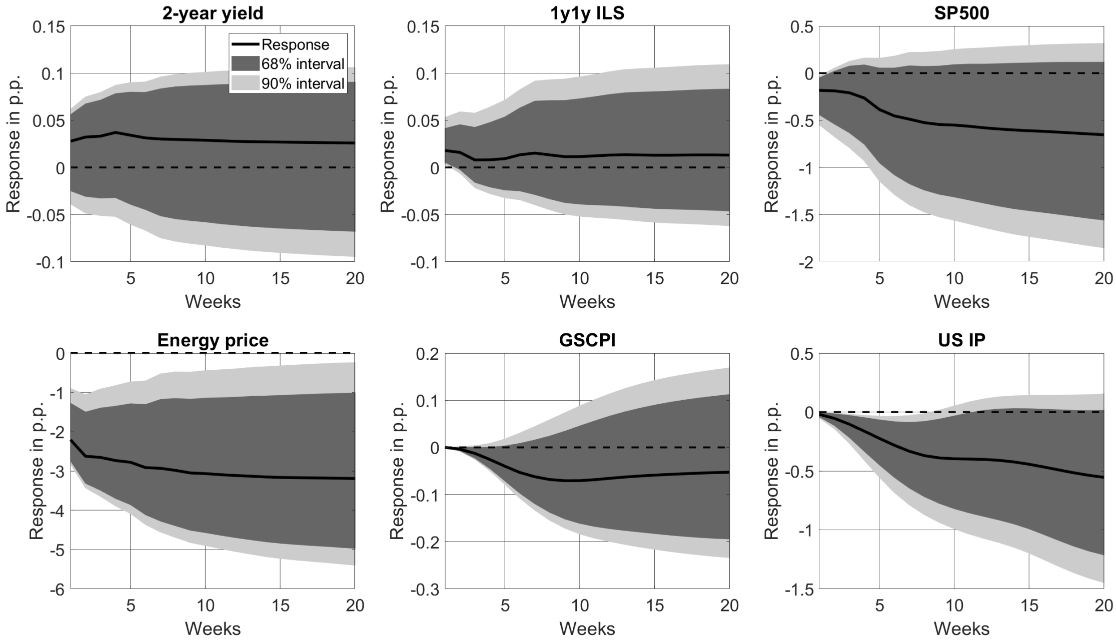

Figure C.14: Impulse responses to a domestic supply shock using the 2-year yield.
Notes: the figure reports the median (black solid line) response to an contractionary supply shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals. Responses are computed using 1000 draws from the posterior of Equation (2). The 2-year instead of the 10-year yield is used.

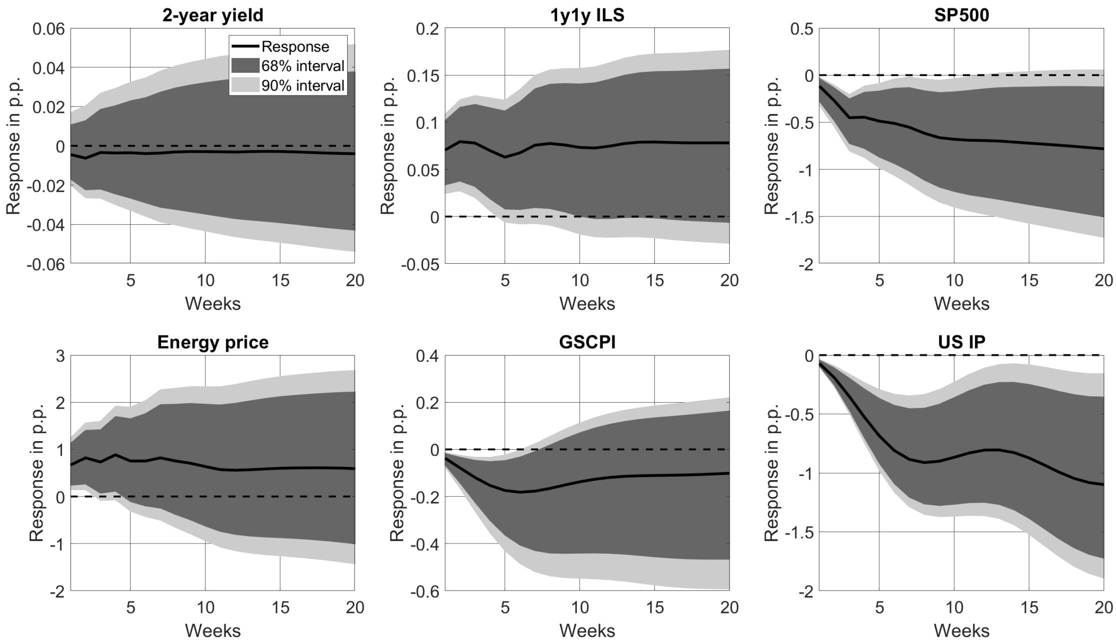

Figure C.15: Impulse responses to an energy supply shock using the US 2-year yield.
Notes: the figure reports the median (black solid line) response to an contractionary energy shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals. Responses are computed using 1000 draws from the posterior of Equation (2). The 2-year instead of the 10-year yield is used.

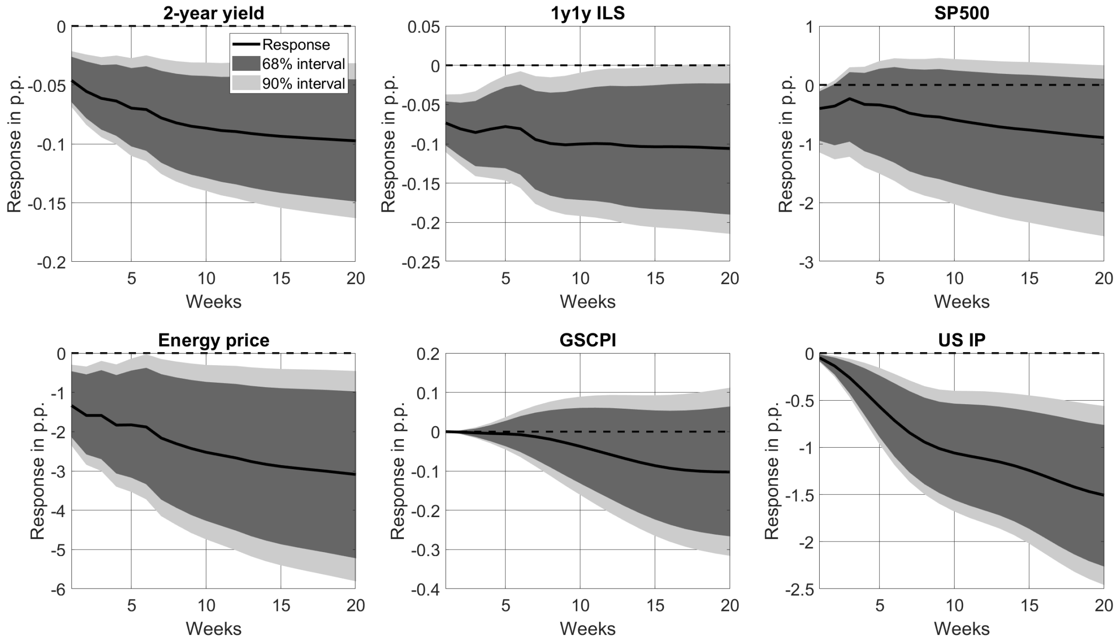

Figure C.16: Impulse responses to a macroeconomic shock using the 2-year yield.
Notes: the figure reports the median (black solid line) response to an expansionary macroeconomic shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals. Responses are computed using 1000 draws from the posterior of Equation (2). The 2-year instead of the 10-year yield is used.

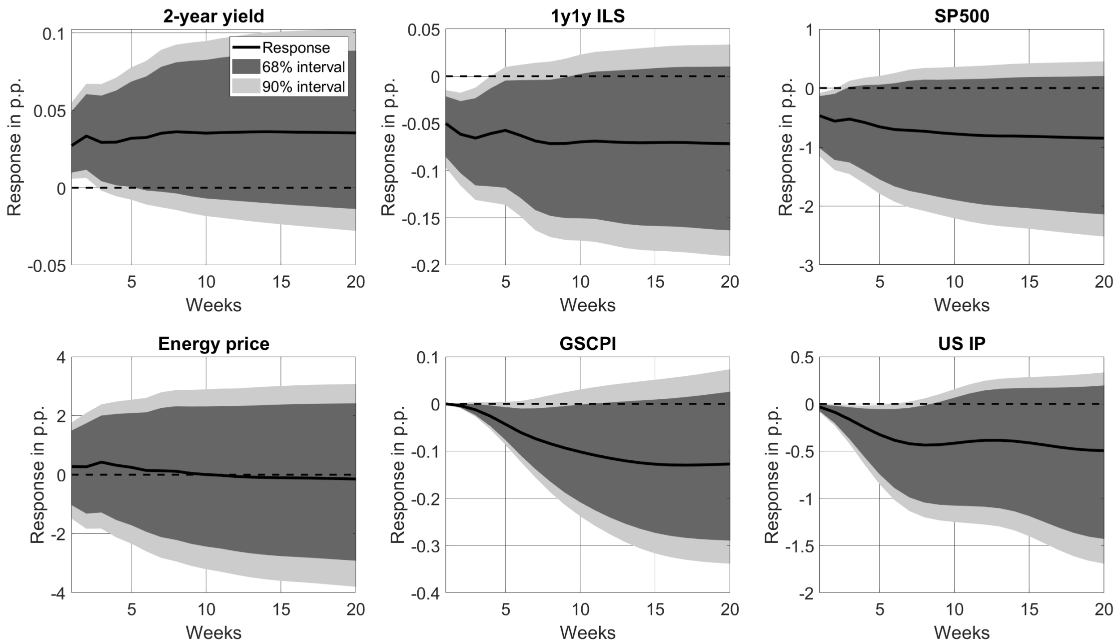

Figure C.17: Impulse responses to a monetary policy shock using the 2-year yield.
Notes: the figure reports the median (black solid line) response to an contractionary monetary policy shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals. Responses are computed using 1000 draws from the posterior of Equation (2). The 2-year instead of the 10-year yield is used.

C.2 Model including the US dollar nominal effective exchange rate

This section reports the main results when the US dollar nominal effective exchange rate (USD Neer) is included as additional high-frequency endogenous variable. The identification scheme remains the same as in Section 3 with the following additional restrictions on the USD Neer: a domestic policy shock appreciates the US dollar while a negative macro shock depreciates it. Furthermore, an additional shock is identified which appreciates the USD Neer, decreases yields, stock prices and inflation expectations. This shock is labeled as "risk shock" as it captures safe haven dynamics that appreciate the dollar but decrease US yields, because of flows into US securities, similar in spirit to Brandt et al. (2026). The shock is also defined to be contractionary.

Table C.3: Forecast error variance decomposition – model with USD Neer

	Macro shock	Monetary policy shock	Energy price shock	GVC supply shock	Domestic supply shock	Risk shock	Unres. shock
				4-weeks horizon			
10-year yield	36.02	15.46	6.55	3.44	9.66	16.24	12.64
1Y1Y ILS	22.71	15.59	12.69	9.90	14.73	15.47	8.91
S&P 500	10.12	17.68	10.16	4.64	15.30	26.75	15.36
Energy price	11.01	15.62	11.48	0.31	17.95	23.36	20.28
USD Neer	8.21	28.35	16.21	3.22	1.08	26.70	16.23
GSCPI Index	0.21	1.00	9.55	67.07	12.07	4.59	5.51
US IP	22.65	11.87	10.98	4.80	11.77	21.27	16.67
				12-weeks horizon			
10-year yield	34.50	15.80	6.97	3.78	9.79	16.45	12.69
1Y1Y ILS	21.81	15.71	12.76	10.01	14.65	15.79	9.27
S&P 500	10.26	17.70	10.35	4.72	15.25	26.31	15.43
Energy price	11.21	15.71	11.69	1.08	17.59	22.74	19.98
USD Neer	8.65	27.70	15.96	3.48	1.83	26.21	16.17
GSCPI Index	2.74	2.45	9.47	63.38	11.09	4.93	5.93
US IP	25.29	10.72	9.91	6.30	11.41	19.89	16.46

Notes: forecast error variance decomposition at the 12 weeks (1-quarter) horizon. The US dollar nominal effective exchange rate is added as high-frequency endogenous variable and an additional Risk shock is identified. The risk shock appreciates the USD Neer, decreases yields, stock prices and inflation expectations.

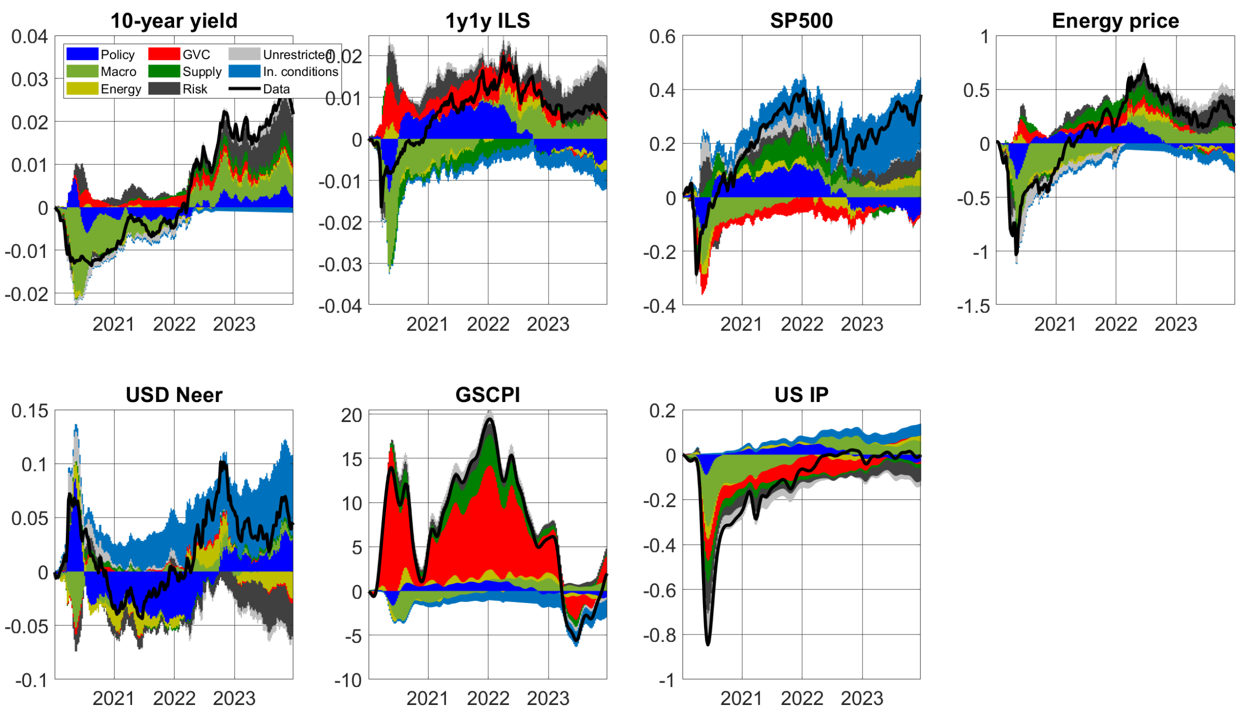

Figure C.18: Historical decomposition between January 2020 and March 2024 including USD Neer.

Notes: the figure reports the median historical decomposition for the period between January 2020 and March 2024. The black line reports the cummulated percentage changes of each variable, standardized to zero at the first observation. Contributions are computed using 1000 draws from the posterior of Equation (2). The US dollar nominal effective exchange rate is added as high-frequency endogenous variable and an additional Risk shock is identified. The risk shock appreciates the USD Neer, decreases yields, stock prices and inflation expectations.

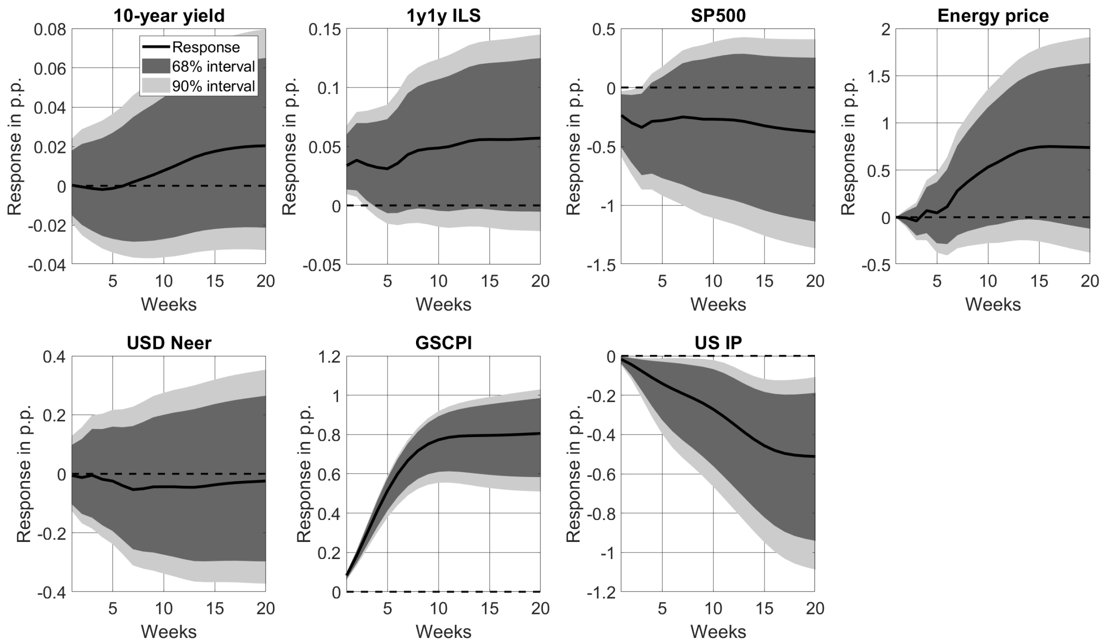

Figure C.19: Impulse responses to a global value chain shock including the USD Neer.
Notes: the figure reports the median (black solid line) response to an contractionary supply shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals. Responses are computed using 1000 draws from the posterior of Equation (2). The US dollar nominal effective exchange rate is added as high-frequency endogenous variable and an additional risk shock is identified. The risk shock appreciates the USD Neer, decreases yields, stock prices and inflation expectations.

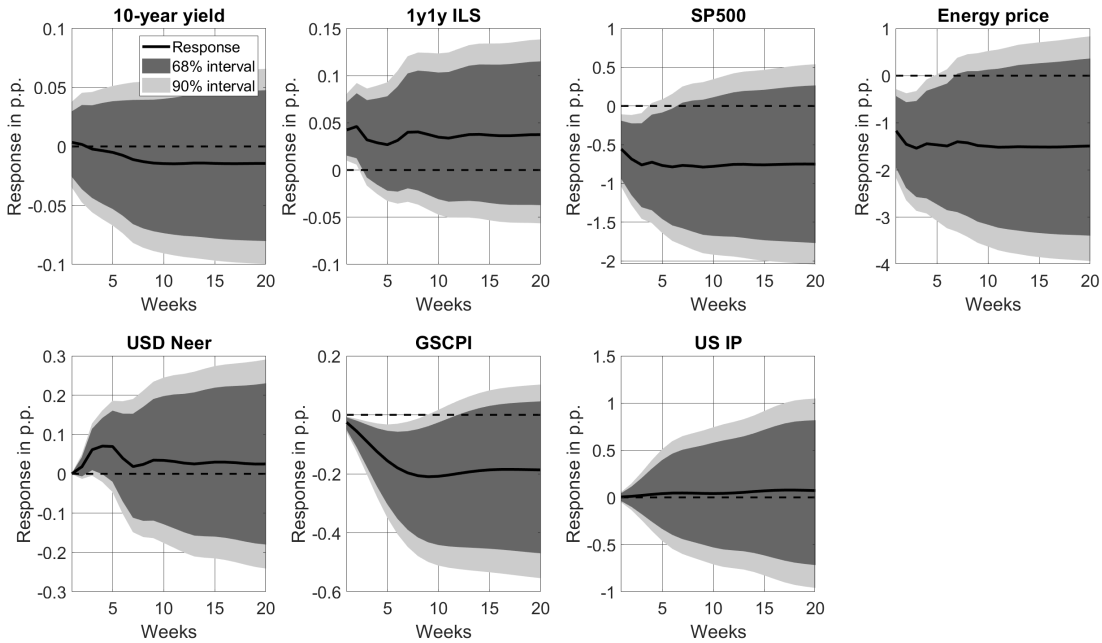

Figure C.20: Impulse responses to a domestic supply shock including the USD Neer.
Notes: the figure reports the median (black solid line) response to an contractionary supply shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals. Responses are computed using 1000 draws from the posterior of Equation (2). The US dollar nominal effective exchange rate is added as high-frequency endogenous variable and an additional risk shock is identified. The risk shock appreciates the USD Neer, decreases yields, stock prices and inflation expectations.

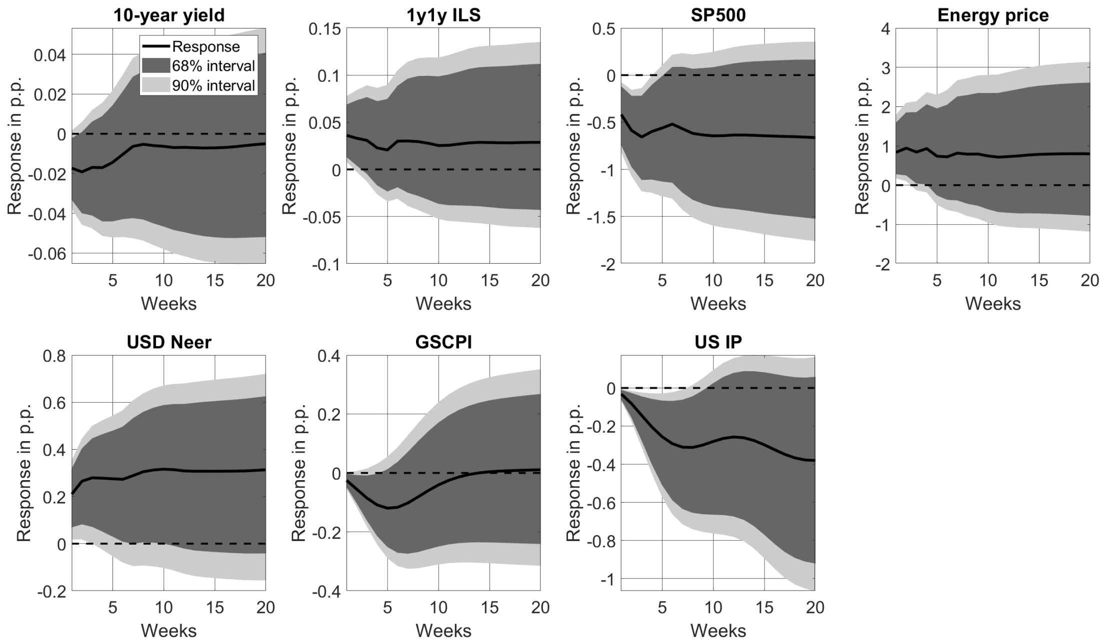

Figure C.21: Impulse responses to a energy supply shock including the USD Neer.
Notes: the figure reports the median (black solid line) response to an contractionary energy shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals. Responses are computed using 1000 draws from the posterior of Equation (2). The US dollar nominal effective exchange rate is added as high-frequency endogenous variable and an additional risk shock is identified. The risk shock appreciates the USD Neer, decreases yields, stock prices and inflation expectations.

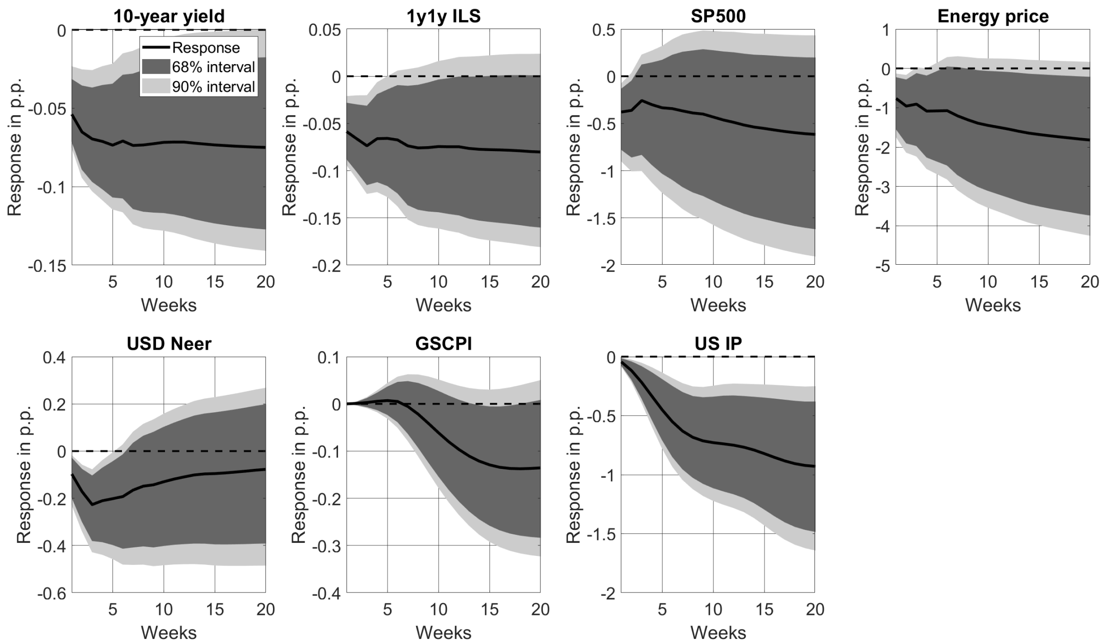

Figure C.22: Impulse responses to a macroeconomic shock including the USD Neer.
Notes: the figure reports the median (black solid line) response to an expansionary macroeconomic shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals. Responses are computed using 1000 draws from the posterior of Equation (2). The US dollar nominal effective exchange rate is added as high-frequency endogenous variable and an additional risk shock is identified. The risk shock appreciates the USD Neer, decreases yields, stock prices and inflation expectations.

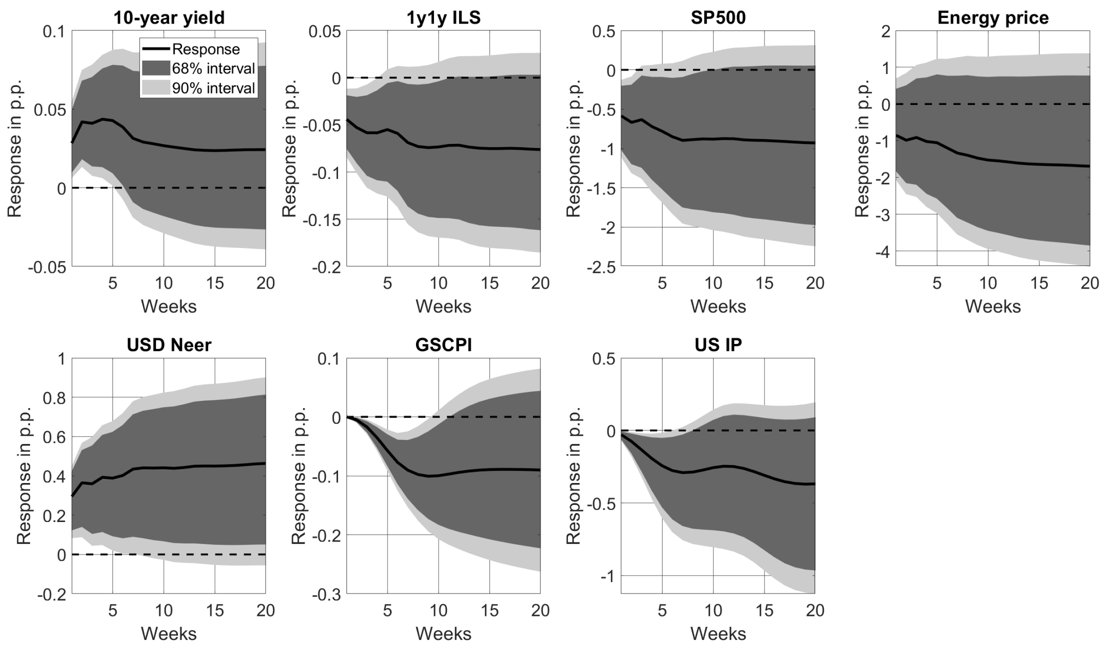

Figure C.23: Impulse responses to a monetary policy shock including the USD Neer.

Notes: the figure reports the median (black solid line) response to an contractionary monetary policy shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals. Responses are computed using 1000 draws from the posterior of Equation (2). The US dollar nominal effective exchange rate is added as high-frequency endogenous variable and an additional risk shock is identified. The risk shock appreciates the USD Neer, decreases yields, stock prices and inflation expectations.

C.3 Model estimated on data up to 2019

This section reports the main results using only data up to 2019 for the estimation – therefore excluding completely the Covid-19 pandemic outbreak and recovery as well as the inflation surge of 2022. The identification scheme remains the same as in Section 3.

Table C.4: Forecast error variance decomposition – sample ending in 2019

	Macro shock	Monetary policy shock	Energy price shock	GVC supply shock	Domestic supply shock	Unres. shock
			4-weeks horizon			
10-year yield	33.54	15.79	12.65	7.92	17.52	12.57
1Y1Y ILS	38.81	19.68	11.84	6.34	12.03	11.30
S&P 500	13.80	10.85	10.00	13.84	5.54	45.97
Energy price	23.99	15.98	3.27	0.36	36.98	19.42
GSCPI Index	0.84	0.93	25.05	63.19	0.67	9.33
US IP	15.75	11.82	25.97	2.60	9.19	34.67
			12-weeks horizon			
10-year yield	31.51	15.96	12.47	8.73	17.26	14.07
1Y1Y ILS	37.83	19.80	11.84	6.91	12.06	11.56
S&P 500	14.24	11.33	10.19	13.54	6.61	44.10
Energy price	23.91	16.37	3.82	1.10	35.80	19.00
GSCPI Index	4.32	3.20	19.39	61.55	2.25	9.29
US IP	21.95	10.10	21.12	7.68	9.73	29.44

Notes: forecast error variance decomposition at the 12 weeks (1-quarter) horizon. The sample ends in 2019.

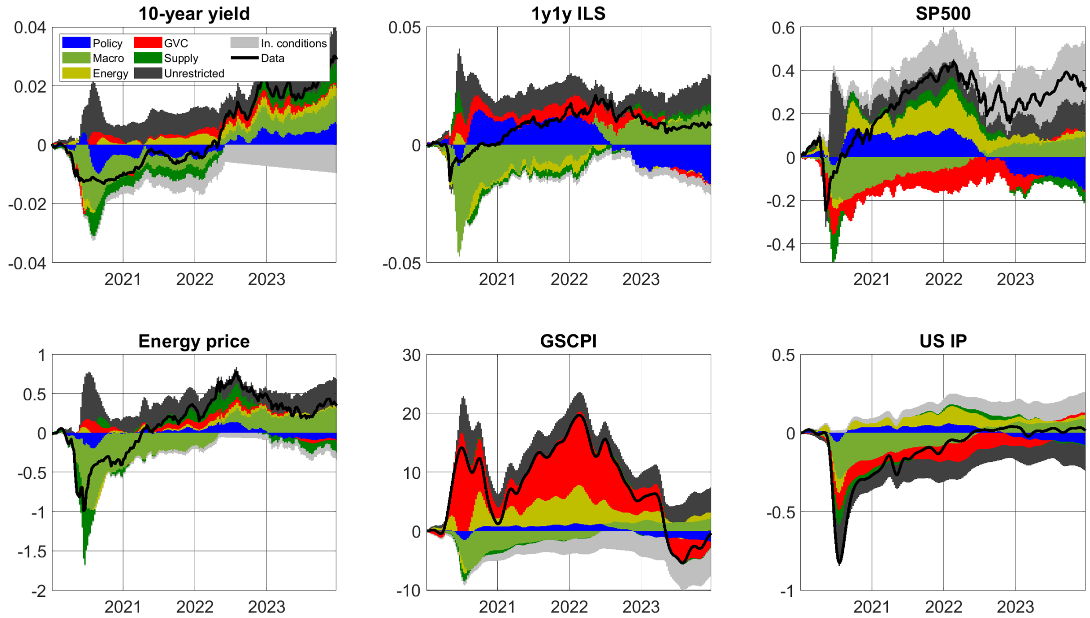

Figure C.24: Historical decomposition between January 2020 and March 2024 using data up to December 2019.

Notes: the figure reports the median historical decomposition for the period between January 2020 and March 2024. The black line reports the cummulated percentage changes of each variable, standardized to zero at the first observation. Contributions are computed using 1000 draws from the posterior of Equation (2). The sample ends in 2019.

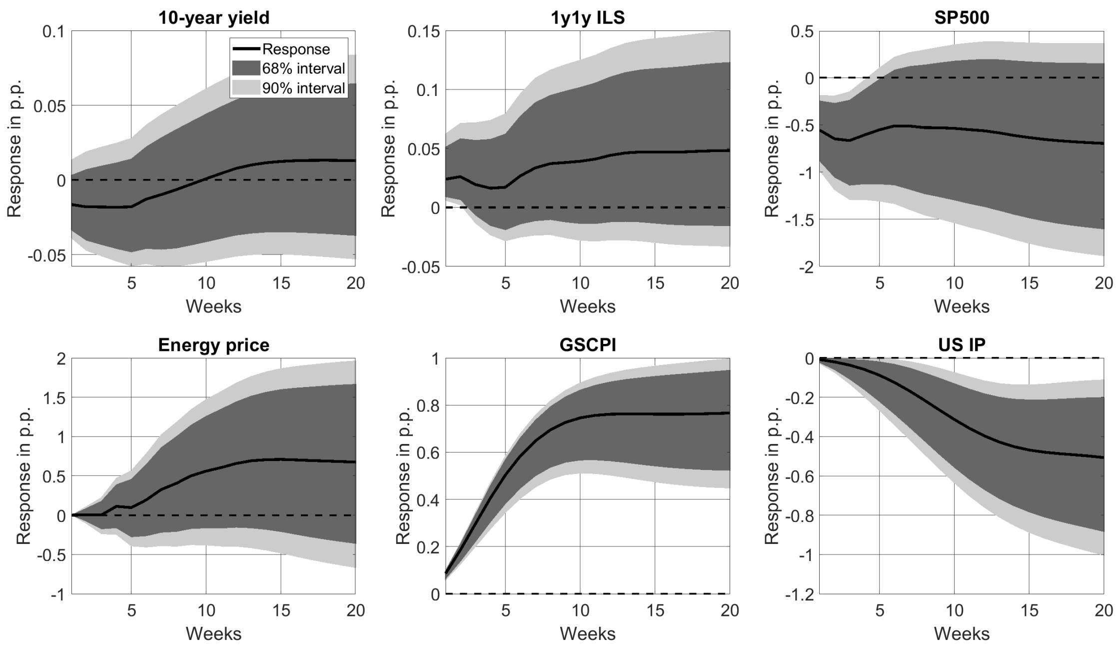

Figure C.25: Impulse responses to a global value chain shock using data up to December 2019.

Notes: the figure reports the median (black solid line) response to an contractionary supply shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals. Responses are computed using 1000 draws from the posterior of Equation (2). The sample ends in 2019.

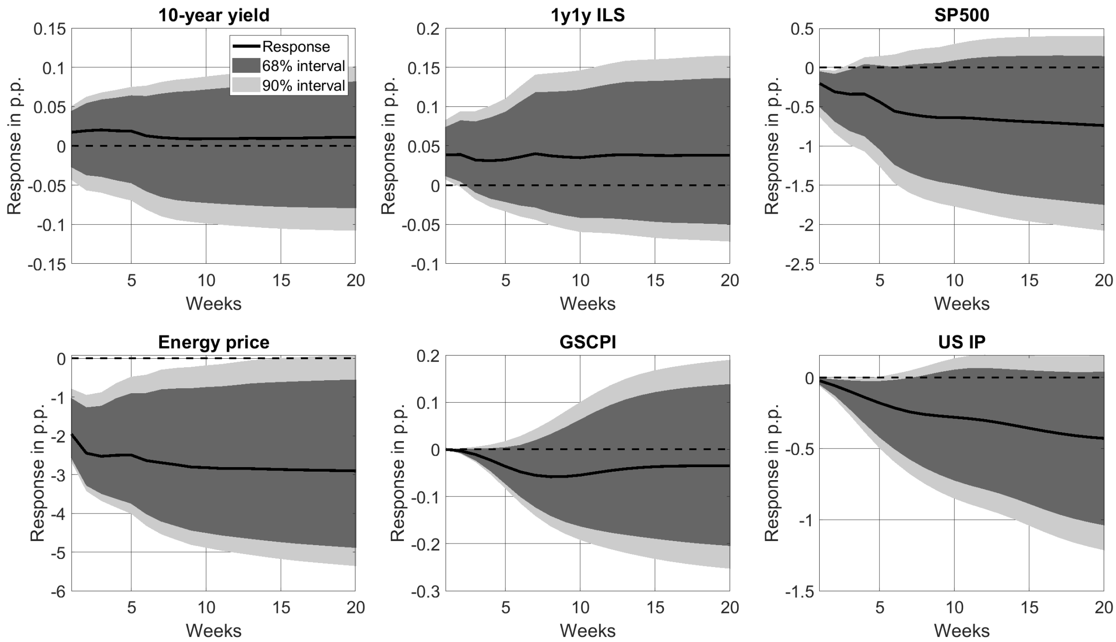

Figure C.26: Impulse responses to a supply shock using data up to December 2019.
Notes: the figure reports the median (black solid line) response to an contractionary supply shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals. Responses are computed using 1000 draws from the posterior of Equation (2). The sample ends in 2019.

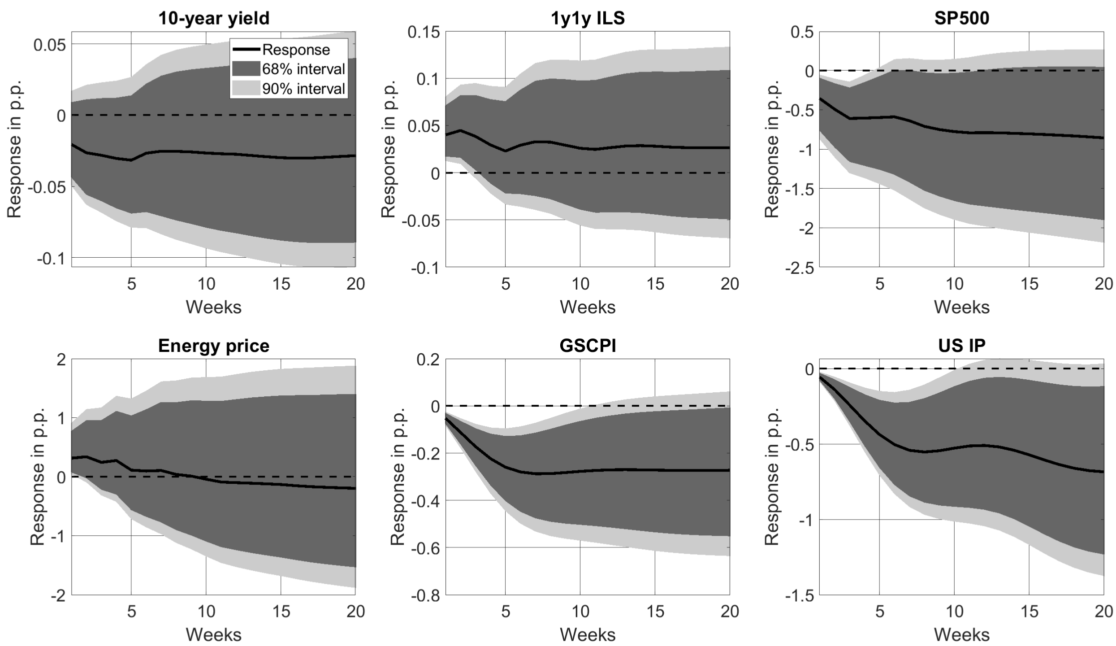

Figure C.27: Impulse responses to a energy shock using data up to December 2019.
Notes: the figure reports the median (black solid line) response to an contractionary energy shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals. Responses are computed using 1000 draws from the posterior of Equation (2). The sample ends in 2019.

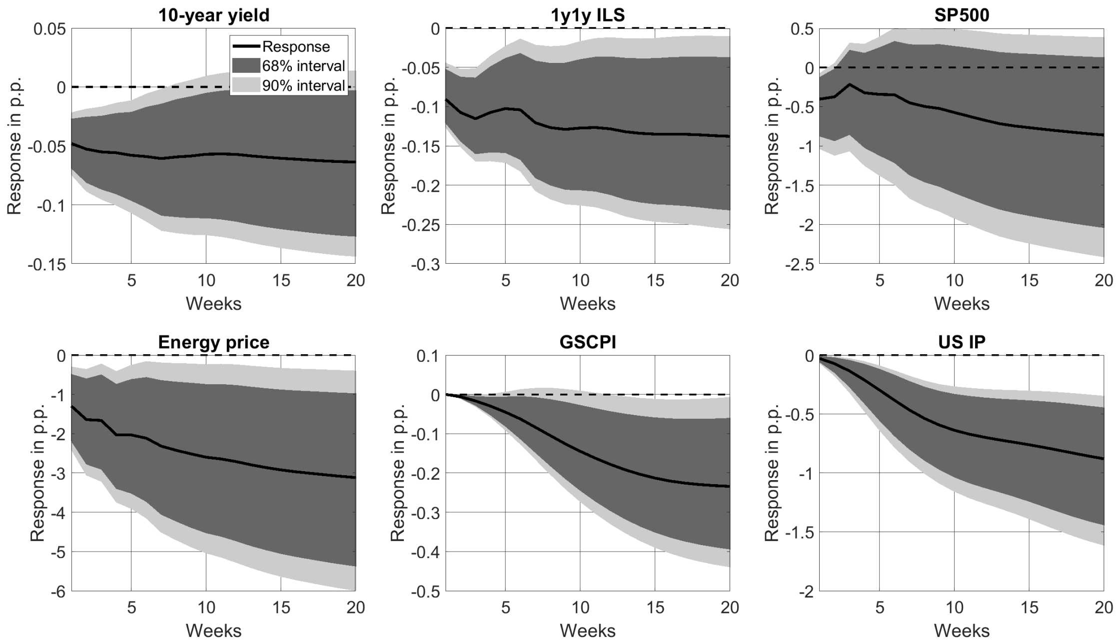

Figure C.28: Impulse responses to a macroeconomic shock using data up to December 2019.

Notes: the figure reports the median (black solid line) response to an expansionary macroeconomic shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals. Responses are computed using 1000 draws from the posterior of Equation (2). The sample ends in 2019.

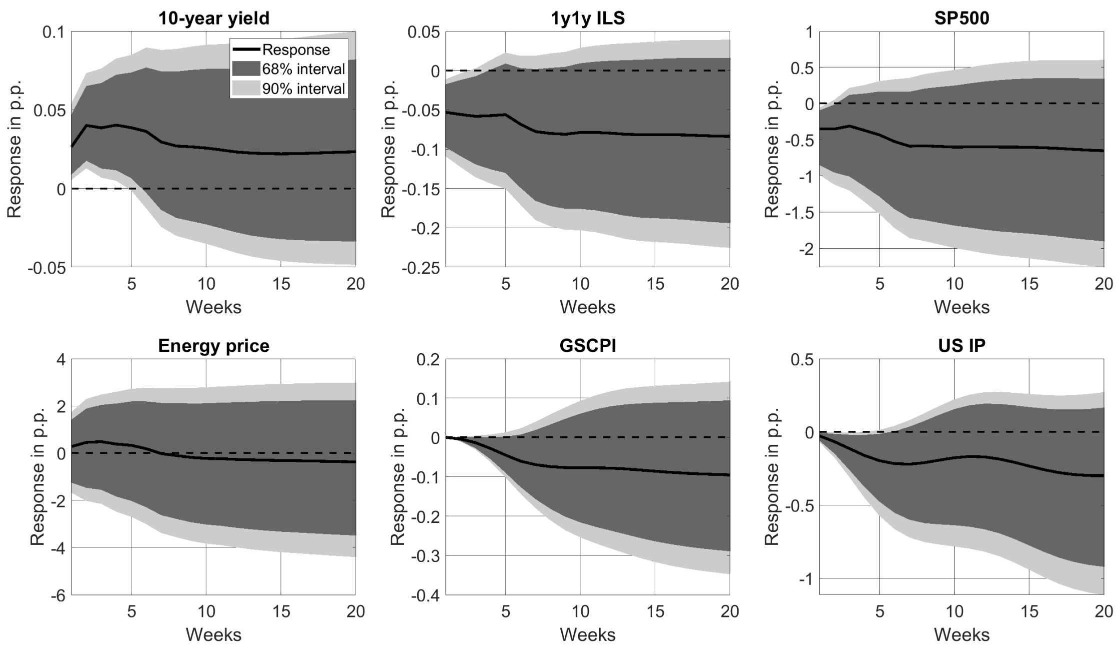

Figure C.29: Impulse responses to a monetary policy shock using data up to December 2019.

Notes: the figure reports the median (black solid line) response to an contractionary monetary policy shock along with 68% (dark grey shaded area) and 90% (light grey shaded area) confidence intervals. Responses are computed using 1000 draws from the posterior of Equation (2). The sample ends in 2019.

C.4 Model excluding the low-frequency component

We exclude the low-frequency variables (GSCP Index and US industrial production) from the endogenous variables in the mixed-fequency VAR, to highlight their value added in capturing supply shocks. The identification scheme remains the same as in Section 3 with the only exclusion of restrictions on the low-frequency variables of the model. Only one supply shock can be identified in this model.

Table C.5: 12-weeks forecast error variance decomposition

	Macro shock	Monetary policy shock	Energy price shock	Supply shock
		4-weeks horizon		
10-year yield	20.33	5.67	12.61	61.39
1Y1Y ILS	22.32	12.30	45.67	19.72
S&P 500	70.90	9.79	8.69	10.62
Energy price	42.18	44.89	12.46	0.47
		12-weeks horizon		
10-year yield	21.30	5.99	12.94	59.78
1Y1Y ILS	22.61	12.26	45.51	19.62
S&P 500	70.02	9.94	9.07	10.96
Energy price	42.01	44.28	12.87	0.84

Notes: forecast error variance decomposition at the 4-weeks (1 month) and 12-weeks (1 quarter) horizon. The model is estimated using high-frequency financial variables only.

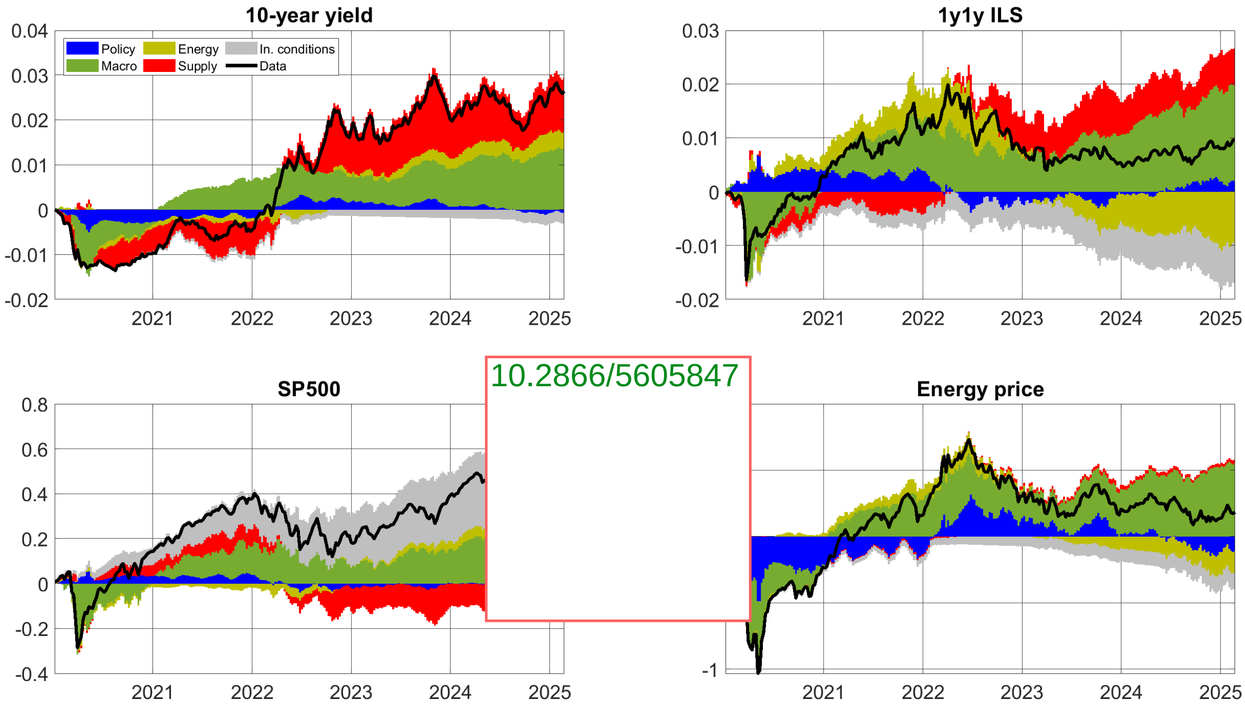

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Figure C.30: Historical decomposition between January 2020 and March 2024 using only weekly financial market data.

Notes: the figure reports the median historical decomposition for the period between January 2020 and March 2024. The black line reports the cummulated percentage changes of each variable, standardized to zero at the first observation. Contributions are computed using 1000 draws from the posterior of Equation (2). Low-frequency variables are not included.

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