Essay on Monentary Policy Spillovers to Emerging Market Economies

Final Work

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December 27, 2024

Abstract

This paper examines the spillover effects of U.S. monetary policy on emerging market economies (EMEs), focusing on the distinction between monetary policy shocks (MP shocks) and central bank information shocks (CBI shocks). Using a panel Bayesian Structural VAR (SVAR) with high-frequency identification, the study isolates the effects of these shocks during Federal Open Market Committee (FOMC) announcements. Results reveal significant heterogeneity in how EMEs respond to these shocks, driven by structural and institutional differences. A Global Bayesian Vector Autoregressive (GBVAR) model is employed to analyze regional transmission patterns, showing that Latin American economies tend to exhibit more pronounced and persistent responses compared to other EMEs. Additionally, an endogenous grouping methodology identifies sub-groups of countries with similar transmission dynamics. These findings underscore the complexities of global monetary spillovers and emphasize the need for policy frameworks in EMEs that account for these heterogeneities.

Keywords: Monetary Policy Spillovers, Emerging Markets.

Contents

1 Introduction

The significant role of the United States in global trade has attracted considerable academic attention to the spillover effects of U.S. monetary policy (e.g., Canova (2005); Uribe and Yue (2006); Rey (2015); Dedola et al. (2017); Miranda-Agrippino and Rey (2020)). Recent research challenges the traditional view that US monetary tightening triggers recessions, currency depreciation, and financial strain in emerging markets (Betts and Devereux, 2000; Vicondoa, 2019). Instead, recent studies indicate that higher US interest rates can lead to a weaker dollar, economic growth, and improved financial conditions in emerging markets (Stavrakeva and Tang, 2019; Ilzetzki and Jin, 2021). In this paper, it is aimed to show the dynamics that are solely caused by the release of US economic information during Federal Open Market Committee's (i.e., FOMC) meetings, following the approaches delineated by Andrade and Ferroni (2016); Jarociński and Karadi (2020).

In particular, it is firstly employed a panel Bayesian SVAR using an identification scheme that allows to separate two FOMC shocks: a pure US monetary policy shock (MP shock) and a central bank information shock (CBI shock). Sign restrictions are applied to the co-movement of high-frequency surprises in various futures contracts (fed funds futures, Eurodollar futures) with maturities ranging from one month to one year and the S&P500 around FOMC meetings. Standard theory unambiguously predicts that a monetary policy tightening shock leads to lower stock market valuations by increasing discount rates and reducing the present value of future dividends and corporate profits. Consequently, monetary policy shocks are identified by negative co-movements between these financial variables. Conversely, positive co-movements between correspond to CBI shocks. Using monthly data of real activity and financial indicators, the first exercise done is analysing every country in the sample (i.e., Brazil; Chile; Colombia; India; Indonesia; Korea; Mexico; Russia; South Africa; Turkey), with results showing considerable heterogeneity across emerging markets in the magnitude and persistence of their responses to these shocks.

Secondly, building on Smith and Galesi (2014), the transmission coefficients are integrated into a global system of equations using a GBVAR approach, which has been applied by few studies so far (e.g., Cimadomo et al. (2020)). To examine regional impacts, the sample is divided into Latin American countries and the Rest of the World. The analysis reveals that Latin American economies generally exhibit sharper and more prolonged responses to monetary policy shocks compared to their global counterparts, underscoring regional sensitivities.

Eventually, following Canova (2007), an endogenous grouping methodology is utilized to identify potential sub-groups within the regional samples that have transmission coefficients with similar means and dispersions. This approach represents a novelty in the current literature, and highlights distinct groupings within the emerging markets, where country-specific characteristics such as financial dollarization and institutional quality shape their responses.

The current work is made up of 6 sections, starting with the present introduction. Section 2 describes the main streams of literature this paper is related to. Section 3 describes the sample and data. Section 4 focuses on the theoretical background, the identification scheme adopted, and the econometric model's methodology. Section 5 reports the results of the panel Bayesian SVAR model. Section 6 concludes, emphasizing the need for tailored monetary policy frameworks in emerging economies to mitigate adverse spillover effects.

2 Literature Review

The current work complements two growing streams of literature: (i) the one focusing on addressing monetary policy non-neutrality and carefully identifying the causal impact of monetary innovations; (ii) the one focusing on the international spillovers of such policies, particularly their effects on Emerging Market Economies (EMEs).

Regarding the first stream, there is a long line of research that attempts to assess the transmission of monetary policy shocks through the adoption of external instruments (Romer and Romer, 2004; Bernanke and Kuttner, 2005; Christiano et al., 2005; Gürkaynak et al., 2005; Gertler and Karadi, 2015; Ramey, 2016; Altavilla et al., 2019; Jarociński and Karadi, 2020; Miranda-Agrippino and Ricco, 2021; Swanson, 2021). This literature seeks to address the fundamental identification challenge arising from the endogenous response of monetary policy to variations in underlying economic fundamentals, aiming to accurately measure structural policy disturbances. The identification of exogenous monetary shocks is crucial to understanding both the magnitude and the channels through which these shocks affect real economic outcomes.

A pioneering contribution in this domain is by Romer and Romer (2000), who show that the Federal Reserve has typically had superior information compared to the private sector, especially regarding inflation forecasts. Building on this insight, Romer and Romer (2004) construct narrative measures of monetary policy shocks by deriving intended federal funds rate changes around FOMC meetings, while controlling for the (private) central bank's internal forecasts of output growth, inflation, and unemployment. In doing so, they disentangle the endogenous policy response from the exogenous innovation to the stance of monetary policy.

Drawing inspiration from the early narrative approaches, after the seminal work of Kuttner (2001); Cochrane and Piazzesi (2002), subsequent studies have increasingly relied on high-frequency identification (HFI) strategies (Gertler and Karadi, 2015; Nakamura and Steinsson, 2018). The key idea behind HFI is that asset price changes around narrow event windows – typically around central bank announcements – reflect unexpected monetary policy surprises, thus mitigating the simultaneity and reverse causality problems. By using high-frequency data from futures contracts (e.g., federal funds futures, Eurodollar futures), these studies isolate plausibly exogenous changes in expectations of future policy rates (Cieslak and Schrimpf, 2019). This approach exploits the fact that in a short time window around policy announcements, other fundamental news is unlikely to drive asset price changes, ensuring that observed price movements can be attributed primarily to monetary policy surprises (Gürkaynak et al., 2005). The availability of such instruments has, in turn, motivated the integration of these surprises into structural vector autoregressions (SVARs) (Stock and Watson, 2012; Mertens and Ravn, 2013; Stock and Watson, 2018) or local projections (Jordà, 2005), thereby mapping policy-induced changes in interest rates to macroeconomic variables such as output and inflation. More recent work, such as Nakamura and Steinsson (2013); Corsetti et al. (2018); Paul (2019), has also incorporated high-frequency measures to analyze global spillovers, often finding heterogeneous responses that depend on institutional and structural features of the receiving economies.

However, a key complication emerges from the fact that policy announcements coincide with central bank communications about the economic outlook. Since market participants might update their forecasts of future fundamentals based on the central bank's assessment, these announcements may embed both monetary policy and information shocks (Romer and Romer, 2000; Barakchian and Crowe, 2013; Campbell et al., 2017). To address this, Jarociński and Karadi (2020) develop an identification scheme that employs sign restrictions and high-frequency data, building on Andrade and Ferroni (2016), to disentangle pure monetary policy shocks from simultaneous central bank information shocks. Their methodology reveals that central bank announcements often convey new information about the state of the economy, which can significantly alter how monetary shocks propagate. This framework has inspired several other contributions, such as Georgiadis and Jarociński (2023) and Kalemli-Özcan and Unsal (2023), who apply similar identification techniques to refine our understanding of the Fed's transmission mechanisms and their international implications (Ahmed et al., 2021; Camara, 2021; Breitenlechner et al., 2022; Jarociński, 2022; Camara et al., 2024). On the other hand, it is worth citing both the work of Miranda-Agrippino and Ricco (2021) and Bauer and Swanson (2022), who respectively incorporate these central bank information effects by removing interest-rate surprises derived from information not publicly available, and exclude public interest-rate surprises to capture unpriced policy responses from misinterpreted central bank actions.

The current work aims to contribute to this growing body of literature by expanding the conventional panel of countries and employing diverse econometric methods to uncover systematic patterns in EMEs' responses to U.S. conventional monetary policy shocks. By doing so, the current work builds on the identification strategies that have increasingly recognized the importance of distinguishing between policy rate surprises and central bank information shocks, while also bringing a richer cross-country perspective to the fore through endogenous grouping methodologies (as in Canova (2007)).

On the second front, our work relates to the literature that examines cross-border monetary spillovers. A common finding is that changes in U.S. monetary policy significantly affect global economic activity (Kim and Roubini, 2000; Kim, 2001; Faust and Rogers, 2003; Canova, 2005; Faust et al., 2007; Bluedorn and Bowdler, 2011) and global financial markets (Neely, 2010; Hausman and Wongswan, 2011; Rogers et al., 2014). More specifically, for EMEs, studies have shown that changes in U.S. interest rates influence local financial conditions, aggregate demand, and macroeconomic stability (Di Giovanni et al., 2017; Azad and Serletis, 2020; Ahmed et al., 2021; London and Silvestrini, 2023). This literature underscores that EMEs are not passive recipients of global financial cycles; instead, their responses can differ substantially depending on domestic characteristics such as exchange rate regimes, capital account openness, domestic financial development, and institutional credibility (Shambaugh, 2004; Miniane and Rogers, 2007).

EMEs often face unique challenges arising from less developed local financial markets, heightened sensitivity to exchange rate fluctuations, and higher levels of financial dollarization (as showed in Georgiadis and Jarociński (2023)). Such conditions can lead to nonlinear and more pronounced responses to external monetary shocks. For instance, abrupt depreciations in local currency can exacerbate balance sheet mismatches, reduce investment incentives, and ultimately undermine growth (Evdokimova et al., 2023). A key finding in the related literature is that U.S. monetary tightening has far-reaching consequences through the so-called global financial cycle, reflecting shifts in global risk appetite and the associated changes in risk premia (Miranda-Agrippino and Rey, 2020; Obstfeld and Zhou, 2023). In this environment, tighter U.S. policy often leads to capital outflows from EMEs, declining asset prices, and overall tighter financial conditions.

In parallel, the literature also considers the "trade channel" of monetary policy spillovers. Theoretically, an increase in U.S. interest rates leads to an appreciation of the U.S. dollar. This relative price shift encourages global demand to pivot away from more expensive U.S. goods toward goods produced elsewhere. Countries experiencing local currency depreciation might initially appear to gain competitiveness. However, if exports are priced in dollars (Gopinath, 2015) or if firms and banks are heavily exposed to unhedged dollar liabilities (Krugman, 1999; Aghion et al., 2001; Schneider and Tornell, 2004; Aguiar, 2005; Kalemli-Özcan et al., 2016), the increase in demand does not necessarily translate into sustained output gains. Rather, the high cost of servicing dollar debts and the tightening of global financial conditions can dominate, leading to muted output responses (Gopinath and Neiman, 2014). Figure 1 illustrates these patterns, as elaborated by Kalemli-Özcan and Unsal (2023).

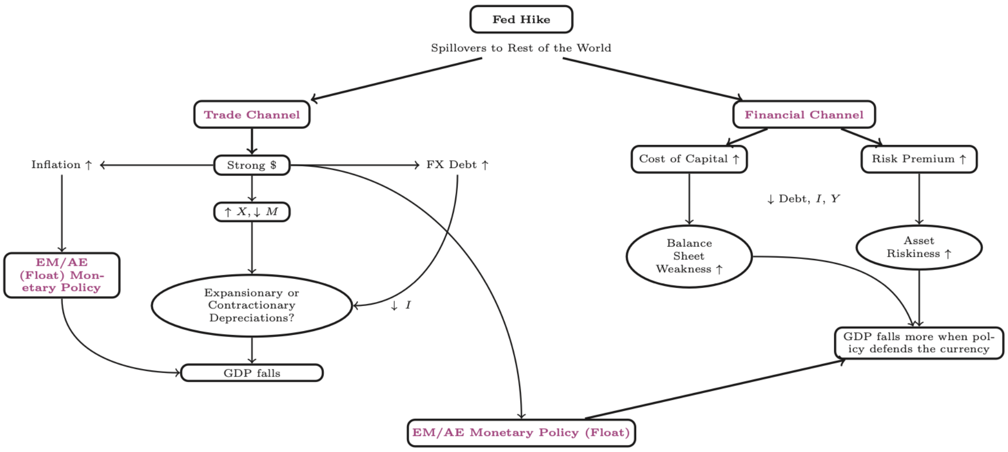


Figure 1: Elaboration by Kalemli-Özcan and Unsal (2023)

This work adds to the above literature by considering a broader set of EMEs, utilizing recently developed econometric tools to capture the complexity of global financial transmission channels and their interaction with local macro-financial features. Our contribution lies in detailing how certain country-specific characteristics, such as the degree of financial dollarization, exchange rate flexibility, institutional quality, and local financial depth, shape the real economy's response to U.S. monetary policy changes. By exploring these dimensions, we aim to offer new insights and a more nuanced understanding of the heterogeneous nature of international spillovers and the underlying mechanics that drive them.

3 Data

The base dataset is an updated version of the Gürkaynak et al. (2005), Swanson (2016), and Jarociński and Karadi (2020) ones. Since 1994, the Federal Open Market Committee (FOMC) has regularly issued press releases regarding its policy decisions and evaluations of financial markets and the economy. These announcements typically occur around 14:00 on the day of the meeting.

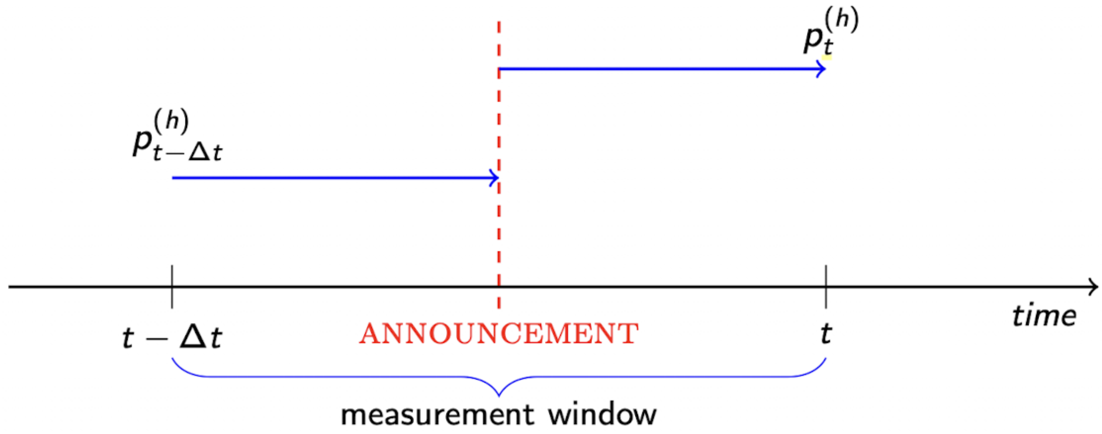


Figure 2: Elaboration based on Gürkaynak et al. (2005)

The primary measure of interest rate surprises is the variable $pc1$ represents the first principal component extracted from a set of high-frequency surprise measures of short-term interest rates derived from various futures contracts with maturities ranging from one month to one year, specifically $MP1$, $FF4$, $ED2$, $ED3$, and $ED4$. It thus provides a parsimonious statistical summary capturing the dominant pattern of unexpected monetary policy shifts embedded in these closely related financial instruments. The $FF4$ surprises reflect changes in three-month federal funds futures, a horizon that generally spans at least one policy meeting under the prevailing scheduling of the U.S. Federal Reserve. This choice of horizon is designed to capture both realized policy moves and near-term forward guidance, while mitigating the impact of timing surprises, such as an anticipated decision announced at an unscheduled meeting. The $ED2$, $ED3$, and $ED4$ series are derived from Eurodollar futures (they denote changes in the second through fourth Eurodollar futures contracts as in Swanson (2016)) which similarly represent expectations of future short-term interest rates, but across a range of slightly longer maturities, thereby providing a complementary perspective on emerging policy expectations. Finally, $MP1$, constructed following the method of Gürkaynak et al. (2005) from adjacent fed funds futures contracts ($FF1$ and $FF2$), isolates the unanticipated component of monetary policy moves. By combining these measures into a single principal component, $pc1$ offers a comprehensive metric that distills the influence of monetary policy surprises on near-term interest rate expectations, thereby facilitating refined empirical investigations into how policy shocks reverberate through financial markets and economic outcomes. On the other hand, the baseline measure for stock price surprises is the change in the S&P500 index, which represents a broad cross-section of 500 large companies. The sample is monthly, from January 2008 to May 2024.

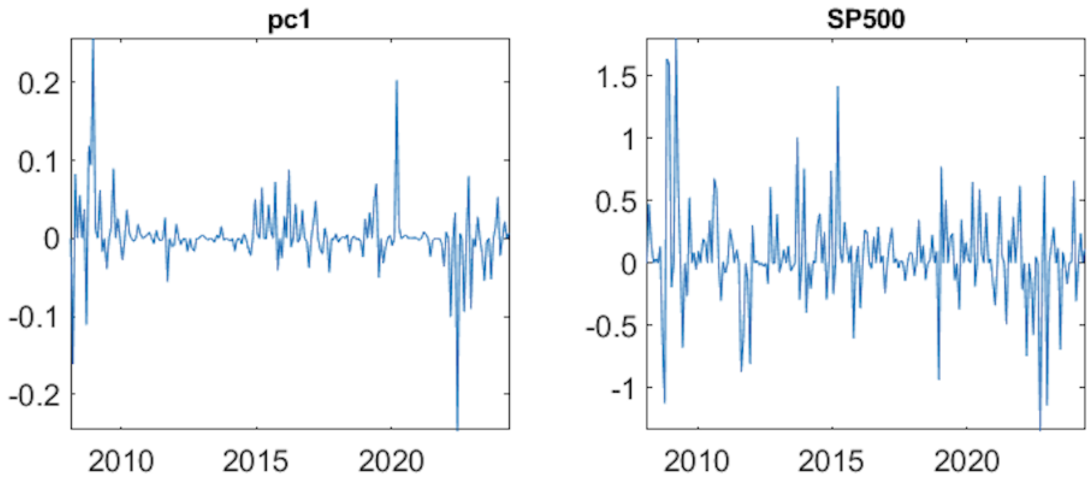


Figure 3: Interest rate and stock price surprises.

The macroeconomic variables analysed are similar to the ones used in both Coibion (2012) and Ramey (2016) – GDP (log levels), GDP Deflator (log levels), and employment (percent). Since the first two values are only available quarterly, the monthly values are obtained by linear interpolation. Additionally, also financial variables are included in the analysis – country major index (log levels) and 1 year government yield (percent).

The countries analysed are the following: Brazil; Chile; Colombia; India; Indonesia; Korea; Mexico; Russia; South Africa; Turkey.

4 The econometric approach

4.1 Identification Strategy

Drawing on Andrade and Ferroni (2016) and Jarociński and Karadi (2020), the current work distinguishes between monetary policy shocks and information shocks by focusing on the relationship between interest rates and stock prices in a narrow window around policy announcements. Conventional theory predicts that tighter monetary policy reduces stock market valuations, as higher discount rates lower the present value of future dividends and diminish the economic outlook.

However, as mentioned above, the observed correlation is not always negative, suggesting that a recurring information shock may emerge at the time of central bank announcements. To identify two structural shocks – the negative co-movement shock and the positive co-movement shock – the current work imposes two assumptions, following Jarociński and Karadi (2020). First, under high-frequency identification, announcement surprises are driven solely by these two shocks, making it unlikely for unrelated events to coincide with the announcement window. Second, applying sign restrictions defines the negative co-movement shock as one that increases interest rates and reduces stock prices, while the positive co-movement shock increases both. Ensuring orthogonality between these shocks is standard for identifying distinct structural disturbances.

Variable	*Shock*		
	Monetary policy (*negative co-movement*)	CB information (*positive co-movement*)	Other
m_t			
Interest rate	+	+	0
Stock index	−	+	0
y_t	•	•	•

Table 1: Sign restrictions in the SVAR model

Note: Restrictions on the contemporaneous responses of variables to shocks. +, −, 0, and • denote positive, negative, zero, and unrestricted responses, respectively. The notation has the following meaning: y_t is a vector of N_y macroeconomic and financial variables observed in month t. On the other hand, m_t is a vector of surprises in N_m financial instruments observed in month t.

The above identification strategy that has been just described is consistent with the analysis provided by Miranda-Agrippino and Ricco (2021), who examine the identification problems of monetary policy shocks through models of imperfect and asymmetric information. Consider each period t, which is divided into an opening stage t^0 and a closing one t^1. At time t^0, private agents receive noisy signals s_{i,t^0} about the economy x_t (i.e., a vector of macroeconomic fundamentals that follows an $AR(1)$ process [1]) and update their forecasts $F_{i,t^0}x_t$ using a Kalman filter. For any $h > 0$,

$$\begin{aligned} F_{i,t}x_t &= K_1 s_{i,t} + (1 - K_1)F_{i,t-1}x_t \\ F_{i,t}x_{t+h} &= \rho^h F_{i,t}x_t \end{aligned} \tag{1}$$

where $F_{i,t}x_t$ denotes the forecast conditional on the information set at time t, and $K1$ is the agents' Kalman gain, which represents the relative weight placed on new information

[1] It follows $x_t = \rho x_{t-1} + \xi_t$, where ξ_t is the vector of structural shocks distributed according to the distribution $\mathcal{N}(0, \Sigma_\xi)$.

relative to previous forecasts. Agents trade future contracts whose price depends on i_{t+h}, the realisation of the policy rate at time $t+h$, proportionally to the current expectation on x_{t+h} (i.e., $p_{t^0}(i_{t+h}) \propto F_{i,t^0}x_{t+h}$). For any $h > 0$,

At time t^1, the Central Bank announces its policy rate i_t based on its forecasts $F_{cb,t^0}x_t$ on the economy. Similarly to the agent, the Central Bank use a Kalman filter to update its forecasts, based on the noisy signal regarding the state of the economy (since the information sets are not the same, the signal s_{cb,t^0} may be divergent from s_{i,t^0}).

$$\begin{aligned} F_{cb,t}x_t &= K_{cb}s_{cb,t} + (1-K_{cb})F_{cb,t-1}x_t \\ F_{cb,t}x_{t+h} &= \rho^h F_{cb,t}x_t \end{aligned} \tag{2}$$

where K_{cb} is the Central Bank' Kalman gain. The Taylor rule[2] used by the Central Bank to set the interest rate i_t takes into account both $F_{cb,t}x_t$ and u_t, the monetary policy shock. Private agents observe i_t once announced at time t^1. Notice that this is equivalent to observing a public signal conditional on i_{t-1} that agents extract from the interest rate decision: assuming that $s_{cb,t^0} = x_t + \eta_{t^0}$, with $\eta_{t^0} \sim \mathcal{N}(0, \sigma_{cb,t^0})$, we see that[3]:

$$\begin{aligned} i_t &= \phi_0 + \phi_x^{'} F_{cb,t^0}x_t + u_t \\ &= \phi_0 + \phi_x^{'}\left[K_{cb}s_{cb,t^0} + (1-K_{cb})F_{cb,t-1^1}x_t\right] + u_t \\ &= \phi_0 + \phi_x^{'}\left[K_{cb}s_{cb,t^0} + (1-K_{cb})F_{cb,t-1^1}\rho x_{t-1}\right] + u_t \\ &= \phi_0 + \phi_x^{'}K_{cb}s_{cb,t^0} + (1-K_{cb})\rho\left(\phi_x^{'}F_{cb,t-1^1}\rho x_{t-1}\right) \\ &= \phi_0 + \phi_x^{'}K_{cb}s_{cb,t^0} + (1-K_{cb})\rho\left(i_{t-1} - \phi_0 - u_{t-1}\right) \\ &= \left[1-(1-K_{cb})\right]\phi_0 + (1-K_{cb})\rho i_{t-1} + \phi_x^{'}K_{cb}s_{cb,t^0} + u_t - (1-K_{cb})\rho u_{t-1} \end{aligned} \tag{3}$$

Thus:

$$\widetilde{s}_{cb,t^1} = x_t + \eta_{t^0} + (K_{cb}\phi_x^{'})^{-1}\left(u_t - (1-K_{cb})\rho u_{t-1}\right) \tag{4}$$

Therefore, agents revise their expectations given the new signal with a new Kalman

[2] It follows $i_t = \phi_0 + \phi_x^{'}F_{cb,t^0}x_t + u_t$.

[3] Assume further that period $t-1$ has the same structure of period t, i.e. an opening stage $t-1^0$ and a closing stage $t-1^1$.

gain K_2:

$$\begin{aligned} F_{i,t}x_t &= K_2\widetilde{s}_{cb,t} + (1-K_2)F_{i,t-1}x_t \\ F_{i,t}x_{t+h} &= \rho^h F_{i,t}x_t \end{aligned} \tag{5}$$

Combining the previous equation, it is evident that the expectations revision $F_{i,t^1}x_t - F_{i,t^0}x_t$ is a function of the public signal and the initial forecast:

$$\begin{aligned} F_{i,t^1}x_t - F_{i,t^0}x_t &= K_2\left[\widetilde{s}_{cb,t^1} - F_{i,t^0}x_t\right] \\ &= K_2\left[x_t + \eta_{t^0} + (K_{cb}\phi_x^{'})^{-1}\left(u_t - (1-K_{cb})\rho u_{t-1}\right)\right] \\ &\quad -K_2F_{i,t^0}x_t \end{aligned} \tag{6}$$

Indeed, the price of future contracts are revised taking into account the new policy rate. The price revision $p_{t^1}(i_{t+1}) - p_{t^0}(i_{t+1})$ is proportional to the expectations revision $F_{i,t^1}x_{t+1} - F_{i,t^0}x_{t+1}$. Here it is trivial to observe that a contractionary monetary policy shock $(u_t > 0)$ which is unanticipated results not necessarily in a reduction of the prices of future contracts.

Building on Ramey (2016)'s critique of Gertler and Karadi (2015)'s high-frequency instruments, which exhibit a notable degree of autocorrelation, it is essential to test instruments for serial correlation. Time dependence represents a significant informational imperfection that can undermine the accuracy of high-frequency identification of monetary policy shocks, as only a fraction of the variation in interest rate forecasts can be uniquely attributed to monetary policy innovations. In this context, the sign restrictions proposed by Jarociński and Karadi (2020) provide a quite robust framework for the accurate identification of these shocks, showing some time dependence only on at lags 6 and 7, 9 and 11. Changing the number of lags does not affect substantially the results.

	Instrument			
	Monetary policy		CB information	
	negative co-movement		*positive co-movement*	
Lag 1	-0.1341*	[0.0699]	0.0183	[0.0730]
Lag 2	-0.0432	[0.0703]	-0.0890	[0.0724]
Lag 3	0.0523	[0.0824]	0.0806	[0.0738]
Lag 4	0.0257	[0.0819]	0.0871	[0.0727]
Lag 5	-0.0687	[0.0812]	-0.1104	[0.0726]
Lag 6	-0.2279***	[0.0813]	0.1589*	[0.0733]
Lag 7	-0.5101***	[0.0780]	-0.0278	[0.0738]
Lag 8	-0.0933	[0.0873]	-0.0497	[0.0730]
Lag 9	-0.0064	[0.0873]	0.1748**	[0.0758]
Lag 10	-0.0018	[0.0989]	0.0229	[0.0749]
Lag 11	-0.0833	[0.0985]	0.2009***	[0.0756]
Lag 12	-0.1628*	[0.0972]	-0.0119	[0.0896]
Constant	-0.0003	[0.0003]	0.0050	[0.0049]
R^2	0.2047		0.1112	
F	4.0329		1.9594	
N	201		201	

Table 2: Autoregressive Component in Instruments à la Jarociński and Karadi (2020) for Monetary Policy Shocks

Note: Values in square brackets represent standard errors. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

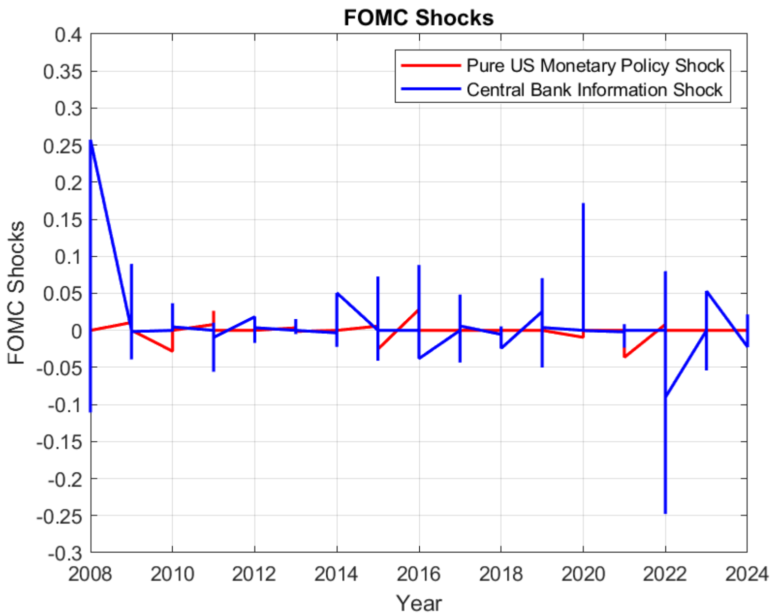


Figure 4: Decomposition of the FOMC shocks in the sample

The figure 4 highlights the predominance of central bank information shocks, largely influenced by the chosen time horizon for the analysis. This period includes significant crises, such as the Great Financial Crisis and the COVID-19 pandemic, during which investors heavily relied on information announced by central bankers (Macklem and Vardy, 2023).

4.2 Model

Vector autoregressive (VAR) techniques are a powerful tool in macroeconomics (Sims (1972)). VARs enable researchers to forecast time series, evaluate economic models, and produce counterfactual policy experiments (Sims (1980)). Nevertheless, for a large number of series, estimating the model using traditional VAR methods runs the risk of over parametrization, as the number of unrestricted parameters is high. The resulting model would likely be unreliable due to overfitting. To account for this concern, a Bayesian approach can be employed. This procedure addresses the "curse of dimensionality" by automatically selecting the degree of shrinkage, using tighter priors when the number of unknown coefficients relative to available data is high, and looser priors otherwise.

Let y_t be a vector of N_y macroeconomic and financial variables observed in month t. Let m_t be a vector of surprises in N_m financial instruments observed in month t[4]. Consider the variable z_t defined as follows:

$$z_t = \begin{pmatrix} m_t \\ y_t \end{pmatrix}$$

The model is a VAR, written in structural form as:

$$A_0 z_t = K + A_1 z_{t-1} + \ldots + A_p z_{t-p} + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, \Sigma_\epsilon) \tag{7}$$

where $A_0, \ldots, A_p$ are matrices of transmission coefficients, and ϵ_t is an n-dimensional vector of structural shocks such that:

$$\epsilon_t = \begin{pmatrix} \epsilon_t^m \\ \epsilon_t^y \end{pmatrix}$$

[4] It is further assumed that m_t does not depend on the lags of either m_t or y_t and has zero mean. This implies that m_t is assumed to be i.i.d.

VARs are estimated in reduced form, i.e.:

$$z_t = C + B_1 z_{t-1} + \ldots + B_p z_{t-p} + u_t, \quad u_t \sim \mathcal{N}(0, \Sigma_u) \tag{8}$$

where $u_t = A_0^{-1}\epsilon_t$, $\mathbb{E}[u_t u_t'] = A_0^{-1}(A_0^{-1})' = \Sigma_u$, and $B_i = A_0^{-1}A_i$. Additionally, $C = A_0^{-1}K$. Moreover, the VAR in 8 can be written in matrix notation as follows (decomposing again Z):

$$\begin{pmatrix} M \\ Y \end{pmatrix} = X \begin{pmatrix} 0 & B \end{pmatrix} + \begin{pmatrix} U^m \\ U^y \end{pmatrix} \tag{9}$$

where $M = (m_1, \ldots, m_T)'$, $Y = (y_1, \ldots, y_T)'$, X is a matrix that collects the right-hand-side variables, with a typical row $x_t' = (m_{t-1}', y_{t-1}', \ldots, m_{t-P}', y_{t-P}', 1)$,

$B = (B_{YM}^1, B_{YY}^1, \ldots, B_{YM}^P, B_{YY}^P, c_Y)'$, $U^m = (u_1^m, \ldots, u_T^m)'$, and $U^y = (u_1^y, \ldots, u_T^y)'$. The Σ_u in 8 can be partitioned:

$$\Sigma = \begin{pmatrix} \Sigma_{MM} & \Sigma_{MY} \\ \Sigma_{YM} & \Sigma_{YY} \end{pmatrix}$$

The likelihood function of M, Y is

$$p(Y, M|B, \Sigma) \propto |\Sigma|^{-T/2} \exp\left(-\frac{1}{2}\mathrm{tr}\left(\left(\begin{pmatrix} M \\ Y \end{pmatrix} - X\begin{pmatrix} 0 & B \end{pmatrix}\right)' \Sigma^{-1} \left(\begin{pmatrix} M \\ Y \end{pmatrix} - X\begin{pmatrix} 0 & B \end{pmatrix}\right)\right)\right)$$

The chosen priors that are standard in the Bayesian VAR literature. In particular, the prior is a Minnesota-type, originally described in Litterman (1979) as described in C, that belongs to the normal-inverse-Wishart family, $p(B, \Sigma) = p(B)p(\Sigma)$, where:

$$p(\Sigma|S, \nu) = \mathcal{IW}(S, \nu) \propto |\Sigma|^{-\nu/2} \exp\left(-\frac{1}{2}\mathrm{tr}(S\Sigma^{-1})\right) \tag{10}$$

$$p(\mathrm{vec}B|B, Q) = \mathcal{N}(\mathrm{vec}B, Q) \propto \exp\left(-\frac{1}{2}\mathrm{vec}(B - \bar{B})'Q^{-1}\mathrm{vec}(B - \bar{B})\right) \tag{11}$$

$\mathcal{IW}$ denotes the Inverted Wishart distribution and $\mathcal{N}$ denotes the normal distribution. The posterior distribution is expressed as the product of the likelihood and the prior:

$$p(B, \Sigma, M \mid Y, M^o) \propto p(Y, M \mid B, \Sigma)p(B)p(\Sigma) \tag{12}$$

Let $t = \tau_1, \ldots, \tau_T^*$ be the period where m_t is not observed. To compute the posterior, a Gibbs sampling method is employed. This method sequentially draws Σ, B, and m_t for $t = \tau_1, \ldots, \tau_T^*$ from their conditional posterior distributions. Convergence is achieved when the sequence of draws sufficiently approximates a sample from the posterior distribution. In the Gibbs sampler it is drawn in turn from three conditional posteriors:

- Firstly, the conditional posterior distribution of Σ is given by:

$$p(\Sigma \mid Y, M, B) = \mathcal{IW}(\bar{S}, \bar{\nu}), \tag{13}$$

  where

$$\bar{S} = \left((M\,Y) - X\begin{pmatrix}0\\B\end{pmatrix}\right)'\left((M\,Y) - X\begin{pmatrix}0\\B\end{pmatrix}\right) + S, \tag{14}$$

$$\bar{\nu} = T + \nu \tag{15}$$

- Secondly, the conditional posterior of B. The likelihood can be decomposed as follows:

$$p(Y, M \mid B, \Sigma) = p(Y \mid M, B, \Sigma)p(M \mid B, \Sigma) \tag{16}$$

  The terms are defined as:

$$\begin{aligned}
p(M \mid B, \Sigma) &= p(M \mid \Sigma_{MM}) \propto |\Sigma_{MM}|^{-T/2} \exp\left(-\frac{1}{2}\mathrm{tr}\, M'M\Sigma_{MM}^{-1}\right) \\
p(Y \mid M, B, \Sigma) &\propto |\Sigma_{YY.1}|^{-T/2} \\
&\quad \exp\Bigg(-\frac{1}{2}\,\mathrm{tr}\bigg(\left(Y - XB + M\Sigma_{MM}^{-1}\Sigma_{MY}\right)' \\
&\quad \Sigma_{YY.1}^{-1}\left(Y - XB + M\Sigma_{MM}^{-1}\Sigma_{MY}\right)\bigg)\Bigg)
\end{aligned} \tag{17}$$

  where $\Sigma_{YY.1} = \Sigma_{YY} - \Sigma_{YM}\Sigma_{MM}^{-1}\Sigma_{MY}$.

- Thirdly, let m_t^* denote the unobserved m_t. Its conditional posterior is:

$$p(m_t^* \mid M^{t-1}, Y, B, \Sigma) = \mathcal{N}\left(\Sigma_{MY}\Sigma_{YY}^{-1}u_t, \Sigma_{MM.1}\right), \tag{18}$$

  where

$$\Sigma_{MM.1} = \Sigma_{MM} - \Sigma_{MY}\Sigma_{YY}^{-1}\Sigma_{YM},$$

M^{t-1} denotes the matrix $(m_{t-1}, \dots, m_0)'$, and

$$u_t = y_t - B'x_t$$

In the current work, once the unit-specific models are estimated, the estimated coefficients are stacked into a global system of equations. The algebraic transformations of the coefficients follows Böck et al. (2020). The unit-specific models are rewritten in terms of the global vector of endogenous variables

$$z_t = \begin{pmatrix} z_{1t}^\top & \cdots & z_{Nt}^\top \end{pmatrix}^\top$$

of dimension $k = \sum_{i=1}^N k_i$.

A unit-specific link matrix W_i $(k_i \times k)$, made up of country-specific weights w_i, is introduced. This is constructed taking the last 10 years average (of the analysis time horizon) of the export shares of each country to U.S. Although this is not an optimal index, it can be a reasonable proxy for foreign exposures. Similarly, in GVAR application (such as in Smith and Galesi (2014)), trade shares are used to weight foreign variables. As a result, the weights are assumed to be constant over time. This results in: The individual models are given by:

$$A_{i0}W_i z_t = a_{i0} + A_{i1}W_i z_{t-1} + \cdots + A_{ip}W_i x_{t-p} + \epsilon_{it},$$

for $i = 0, 1, 2, \dots, N$, and these individual models are then stacked to yield the model for z_t given by:

$$G_0 z_t = a_0 + G_1 z_{t-1} + \cdots + G_p z_{t-p} + \epsilon_t$$

where:

$$G_0 = \begin{pmatrix} A_{00}W_0 \\ A_{10}W_1 \\ \vdots \\ A_{N0}W_N \end{pmatrix}, \quad G_j = \begin{pmatrix} A_{0j}W_0 \\ A_{1j}W_1 \\ \vdots \\ A_{Nj}W_N \end{pmatrix} \quad \text{for } j = 1, \dots, p,$$

$$a_0 = \begin{pmatrix} a_{00} \\ a_{10} \\ \vdots \\ a_{N0} \end{pmatrix}, \quad a_1 = \begin{pmatrix} a_{01} \\ a_{11} \\ \vdots \\ a_{N1} \end{pmatrix}, \quad \epsilon_t = \begin{pmatrix} \epsilon_{0t} \\ \epsilon_{1t} \\ \vdots \\ \epsilon_{Nt} \end{pmatrix}$$

Mixed-frequency BVARs are also effective for identifying shocks and analyzing their transmission mechanisms. They retain one of the key advantages of VAR models while offering the additional benefit of enabling analysis at a monthly frequency (Cimadomo et al., 2020).

In Section 5, for illustrative reasons, impulse responses are presented. Following Hamilton (1994), impulse responses describe the time path of the effects caused by shocks to specific variables or identified shocks on the future states of a dynamic system, influencing all variables within the model. As underlined in Jarociński and Karadi (2020), the imposition of sign restriction for the first two shocks (and zero to the others) on impulse responses implies a block-Choleski structure on the shocks. So, as done in Rubio-Ramírez et al. (2010), for each draw of model parameters from the posterior, a rotation of the first two Cholesky shocks is identified to satisfy the sign restrictions.

Finally, following the procedure designed by Canova (2007), it is possible to endogenously group cross sectional units and allow for Bayesian estimation of the parameters of the model. The overall idea is that if two units belong to the same group, their coefficient vectors will share the same mean and dispersion. Otherwise, their coefficient vectors will exhibit different statistical moments. Yet, differently from Canova (2007), in the current work a prior for the ordering producing a group is not employed; on the other hand, the Posterior odds ratio is used to identify the number of breaks of the group, and the maximum predictive density of the data given the number of breaks is reported. Let φ be the ordering of the group, and ς be the location of the break in the group. Let $f(Y \mid H_0)$ be the predictive density of data where no breaks are present. Let f^0 be the average predictive density with ς breaks where the average is calculated over all possible locations of the break points. Consequently, the Posterior odd ratio is given by:

$$PO(\varphi) = \frac{f(Y \mid H_0)}{\sum_{\varsigma} f^0(Y \mid H_{\varsigma}, \varphi)}$$

Moreover, verification of the hypothesis that there are $\zeta - 1$ vs. ζ breaks in the cross-section can be done:

$$PO(\zeta, \zeta - 1) = \frac{f^{0(\zeta-1)}(Y \mid H_{\zeta-1}, \varphi)}{f^{0(\zeta)}(Y \mid H_{\zeta}, \varphi)} \tag{19}$$

After identifying the number of break points, units are assigned to groups in a way that maximizes the overall predictive density. This ensures the most effective allocation for achieving the highest predictive accuracy.

All in all, the VAR has 9 lags. The results are based on 4000 draws from the Gibbs sampler, obtained after discarding the first 4000 draws and keeping every fourth of the subsequent 16000.

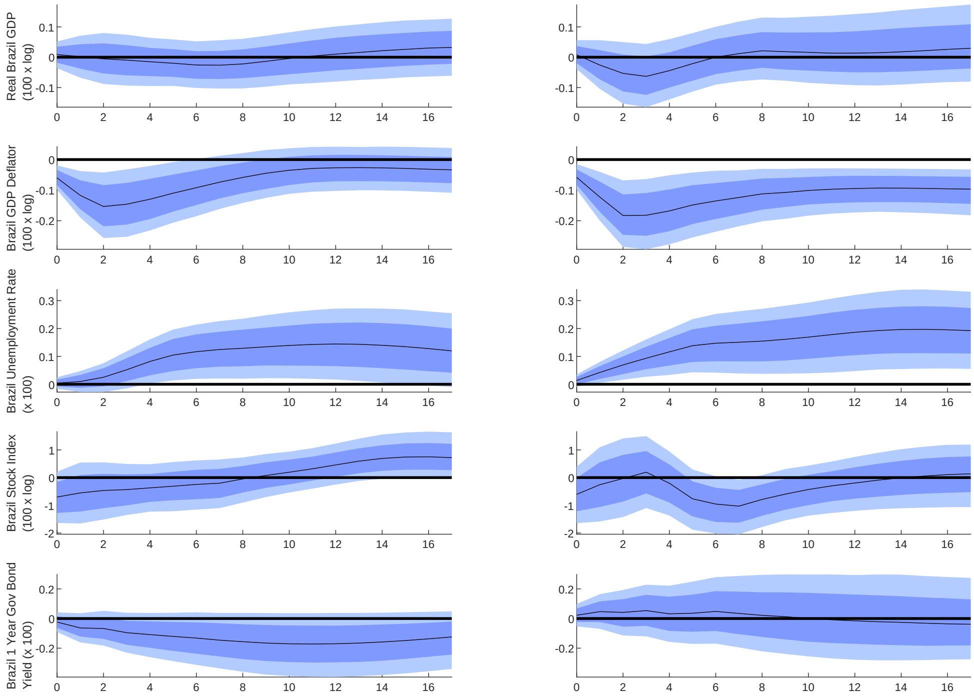
5 Results

5.1 Single Country Impulse Responses

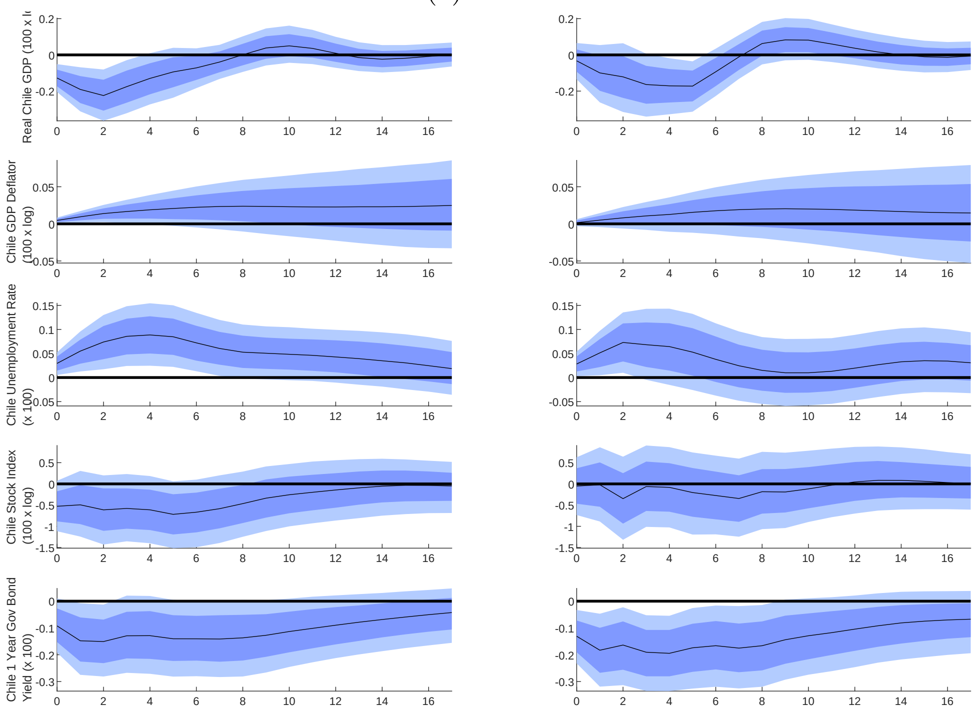
The figures below presents the impulse responses to the monetary policy (left column) and central bank information shocks (right column). Figures 5 and 6 refers to Latin American countries of the panel, whose impulse responses are reported in Table 3 and 4. As in Jarociński and Karadi (2020) and Camara (2021), it can be easily observed that the sign restriction on the high-frequency co-movement of interest rates and stock prices separates two economic shocks, that in some cases are pretty different one from the other.

A prominent feature of the Latin American countries analyzed is the considerable heterogeneity in the magnitude and persistence of their responses to both monetary policy and central bank information shocks. While the directional responses largely align with standard macro-finance theories, the intensity and temporal dynamics exhibit significant variability across countries.

For MP shocks, the contractionary effects on real GDP are evident, as anticipated in conventional monetary theory. For instance, Chile and Brazil display median declines in real GDP of several basis points. In Chile, this decline is relatively persistent, extending across several quarters, whereas Brazil experiences a more transient contraction that reverts to baseline levels within one to two years. In contrast, Colombia and Mexico demonstrate more pronounced and sustained declines in real GDP, highlighting the heterogeneous sensitivities among emerging market economies. Price level responses, captured through the GDP deflator, also decline across the sample, although the magnitude and duration vary significantly, with countries such as Brazil exhibiting sharper adjustments compared to their regional peers.

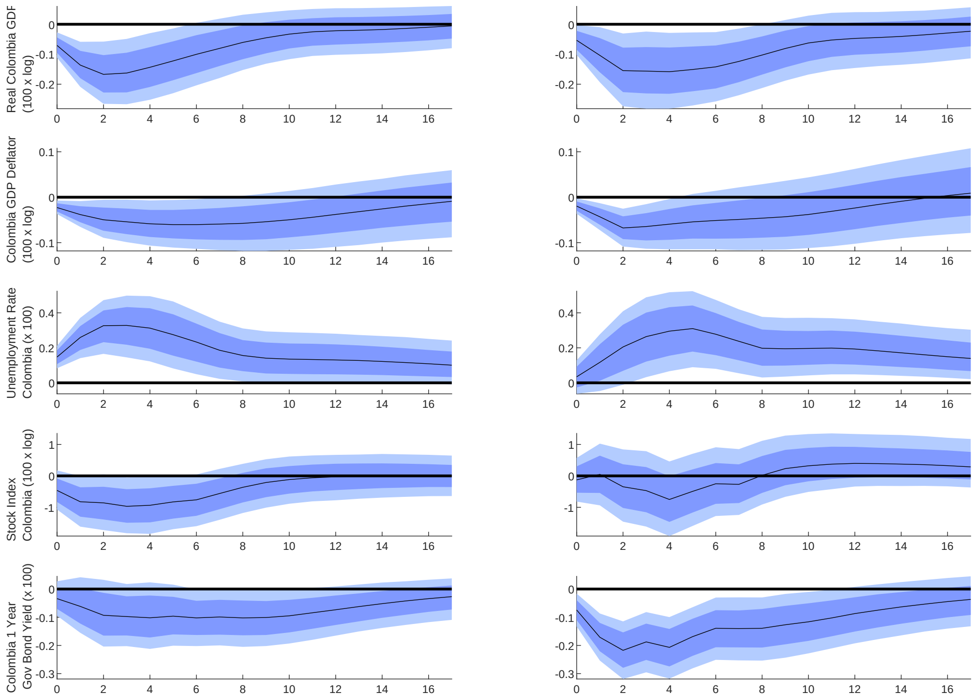


(a) Brazil

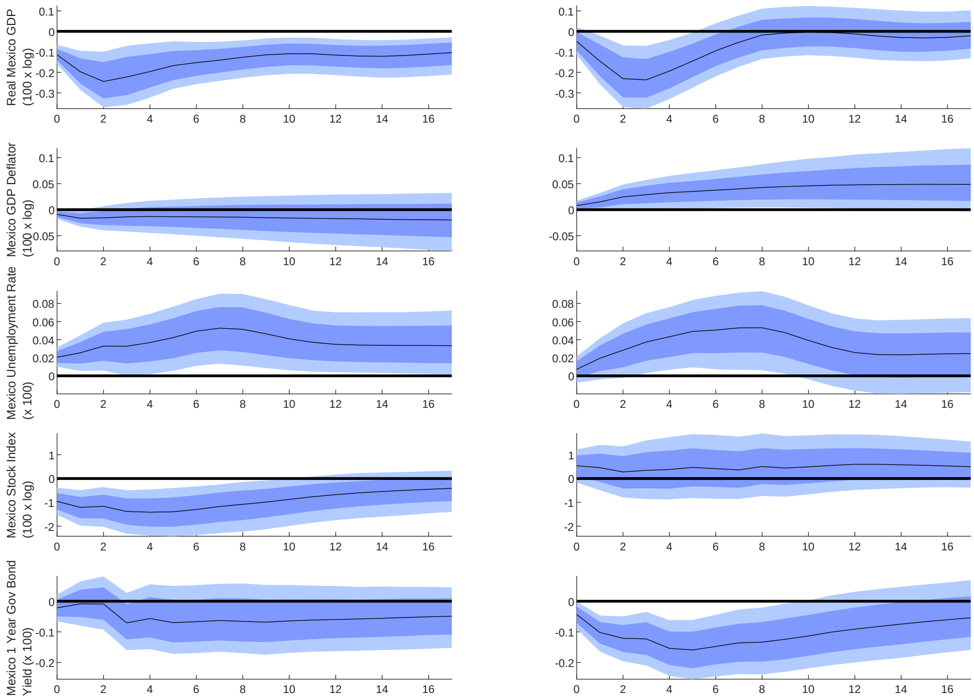


(b) Chile

Figure 5: Impulse responses to one standard deviation shocks for multiple countries. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band).



(a) Colombia



(b) Mexico

Figure 6: Impulse responses to one standard deviation shocks for multiple countries. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band).

The labor market responses, measured via unemployment rates, consistently rise following MP shocks. The median posterior responses for countries such as Colombia and Chile underscore the contractionary nature of monetary tightening, with unemployment increasing by several basis points. On the financial front, MP shocks induce a decline in stock indices and an increase in government bond yields, reflecting a tightening of financial conditions and reduced investor risk appetite. For example, both Chile and Brazil witness notable declines in equity valuations, while bond yields rise as higher borrowing costs and expectations of sustained tightening are priced into financial markets.

The analysis of CB shocks reveals contrasting dynamics compared to MP shocks. While MP shocks lead to persistent declines in price levels, CB shocks are often associated with stable or slightly rising price levels, particularly in the short to medium term. This observation aligns with the hypothesis that CB shocks, which signal improved economic fundamentals, may elevate inflation expectations and actual price growth, prompting subsequent policy adjustments to counterbalance overheating risks. Notably, in some cases, these signaling effects lead to short-run boosts in economic activity, as observed in the posterior distributions for countries such as Brazil and Chile.

The persistence of responses differs markedly between MP and CB shocks. MP shocks generally normalize interest rates and macro-financial variables within one to two years, while CB shocks exhibit longer-lasting impacts on certain dimensions. For instance, the 1-year government bond yield remains elevated for an extended period following a CB shock, reflecting ongoing revisions to market expectations about future monetary policy stances and macroeconomic fundamentals. In terms of price levels, MP shocks tend to induce sharper, albeit less persistent, disinflationary effects compared to the inflationary drift triggered by positive CB shocks. These findings highlight the complexities in interpreting central bank signals and the potential for such signals to influence inflation expectations and economic dynamics over the medium term.

The results underscore the heterogeneous responses of Latin American economies to MP and CB shocks, shaped by country-specific structural and institutional factors. The differential impacts across real, financial, and price-level variables underscore the importance of understanding the nuanced transmission mechanisms of monetary policy spillovers in emerging markets.

Table 3: Quantiles of the posterior distribution - Chile and Brazil

	Chile		Brazil	
Variable	MP (5%,95%)	CB (5%,95%)	MP (5%,95%)	CB (5%,95%)
GDP real	-12.63 (-20.35, -5.43)	-3.18 (-12.93, 7.09)	0.77 (-3.58, 5.21)	0.79 (-3.72, 5.58)
GDP Deflator	0.46 (0.07, 0.86)	0.16 (-0.30, 0.63)	-6.01 (-9.93, -1.99)	-5.93 (-9.99, -1.45)
Unemployment Rate	2.94 (0.55, 5.30)	2.82 (0.15, 5.27)	0.47 (-1.59, 2.56)	1.32 (-0.83, 3.52)
Stock Index	-52.36 (-111.85, 8.56)	-4.52 (-70.92, 63.27)	-72.73 (-162.57, 20.41)	-62.09 (-159.10, 37.82)
Gov. bond yield	-9.25 (-19.58, 1.08)	-13.24 (-23.06, -3.25)	-2.35 (-9.37, 4.34)	2.20 (-4.97, 9.53)

Note: All values are in basis points. Posterior medians and 5th, 95th percentiles. MP = Monetary Policy shock, CB = Central Bank information shock.

Table 4: Quantiles of the posterior distribution - Colombia and Mexico

	Colombia		Mexico	
Variable	MP (5%,95%)	CB (5%,95%)	MP (5%,95%)	CB (5%,95%)
GDP real	-7.06 (-11.16, -2.69)	-5.34 (-10.20, -0.28)	-9.84 (-14.82, -4.50)	-3.82 (-10.72, 3.37)
GDP Deflator	-2.28 (-3.71, -0.73)	-1.96 (-3.64, -0.23)	-0.24 (-1.17, 0.72)	0.52 (-0.49, 1.55)
Unemployment Rate	14.75 (8.33, 21.26)	3.44 (-6.29, 12.89)	1.72 (0.64, 2.76)	0.15 (-1.28, 1.58)
Stock Index	-46.24 (-107.13, 17.38)	-12.61 (-81.74, 57.21)	-99.97 (-163.62, -30.84)	72.85 (-8.26, 146.96)
Gov. bond yield	-3.40 (-9.47, 2.76)	-7.43 (-13.27, -1.62)	-2.68 (-6.47, 1.45)	-5.21 (-8.78, -1.56)

Note: All values are in basis points. Posterior medians and 5th, 95th percentiles. MP = Monetary Policy shock, CB = Central Bank information shock.

Figures 7, 8, and 9 refer to the other countries of the panel, whose impulse responses are reported in Table 5, 6, and 7.

Table 5: Quantiles of the posterior distribution - Russia and Korea (in basis points)

	Russia		Korea	
Variable	MP (5%,95%)	CB (5%,95%)	MP (5%,95%)	CB (5%,95%)
GDP real	-6.21 (-20.92, 7.68)	10.61 (-3.19, 25.02)	-0.63 (-1.77, 0.63)	1.52 (0.50, 2.52)
GDP Deflator	0.11 (-0.79, 1.01)	0.47 (-0.42, 1.44)	-0.27 (-1.14, 0.59)	0.25 (-0.64, 1.15)
Unemployment Rate	2.03 (0.44, 3.59)	2.01 (0.30, 3.63)	-0.14 (-0.94, 0.67)	0.09 (-0.73, 0.93)
Stock Index	-47.92 (-132.69, 34.17)	37.95 (-50.71, 128.49)	-94.06 (-172.18, -3.08)	50.44 (-80.04, 202.77)
Gov. bond yield	14.46 (-1.35, 30.68)	12.07 (-5.76, 29.58)	-2.48 (-5.63, 1.13)	-5.47 (-8.00, -2.97)

Note: All values are in basis points. Posterior medians and 5th, 95th percentiles. MP = Monetary Policy shock, CB = Central Bank information shock.

Table 6: Quantiles of the posterior distribution - India and Turkey (in basis points)

	India		Turkey	
Variable	MP (5%,95%)	CB (5%,95%)	MP (5%,95%)	CB (5%,95%)
GDP real	-11.88 (-25.00, 0.99)	-19.91 (-30.27, -9.23)	-12.28 (-23.84, -0.61)	-4.87 (-8.55, 18.37)
GDP Deflator	0.41 (0.02, 0.77)	0.54 (0.18, 0.90)	-1.93 (-4.97, 1.11)	0.85 (-2.39, 4.22)
Unemployment Rate	-0.23 (-0.69, 0.23)	0.47 (0.04, 0.91)	6.63 (2.39, 10.93)	2.39 (-3.09, 7.64)
Stock Index	-65.14 (-129.22, -1.38)	-21.60 (-94.56, 48.35)	-128.72 (-212.05, -47.29)	-80.00 (-120.37, 100.58)
Gov. bond yield	1.80 (-2.92, 6.54)	-5.41 (-9.75, -1.08)	4.09 (-16.24, 23.54)	-17.00 (-36.51, 2.76)

Note: All values are in basis points. Posterior medians and 5th, 95th percentiles. MP = Monetary Policy shock, CB = Central Bank information shock.

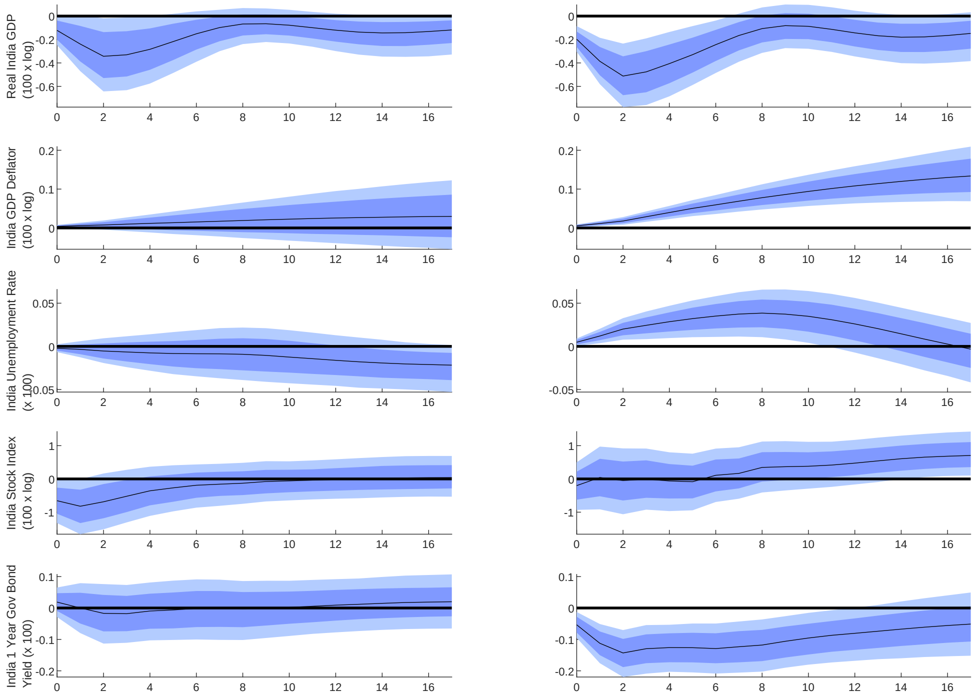
Table 7: Quantiles of the posterior distribution - South Africa and Indonesia (in basis points)

	South Africa		Indonesia	
Variable	MP (5%,95%)	CB (5%,95%)	MP (5%,95%)	CB (5%,95%)
GDP real	-6.58 (-9.78, -3.45)	-7.02 (-12.88, -2.86)	0.46 (-4.47, 5.42)	-4.94 (-9.52, 1.10)
GDP Deflator	-0.17 (-1.24, 0.92)	-1.62 (-6.84, 0.51)	-0.65 (-1.86, 0.58)	-1.63 (-4.24, 1.10)
Unemployment Rate	-3.05 (-6.62, 0.51)	-5.14 (-12.88, 2.68)	1.10 (0.02, 2.14)	0.57 (-4.24, 2.51)
Stock Index	-43.52 (-95.01, 13.28)	11.69 (-18.65, 116.67)	-91.91 (-153.56, -32.59)	-95.21 (-153.56, 59.79)
Gov. bond yield	-0.65 (-6.84, 5.36)	-12.88 (-18.65, -2.86)	-2.67 (-9.52, 4.09)	-4.24 (-12.88, 10.36)

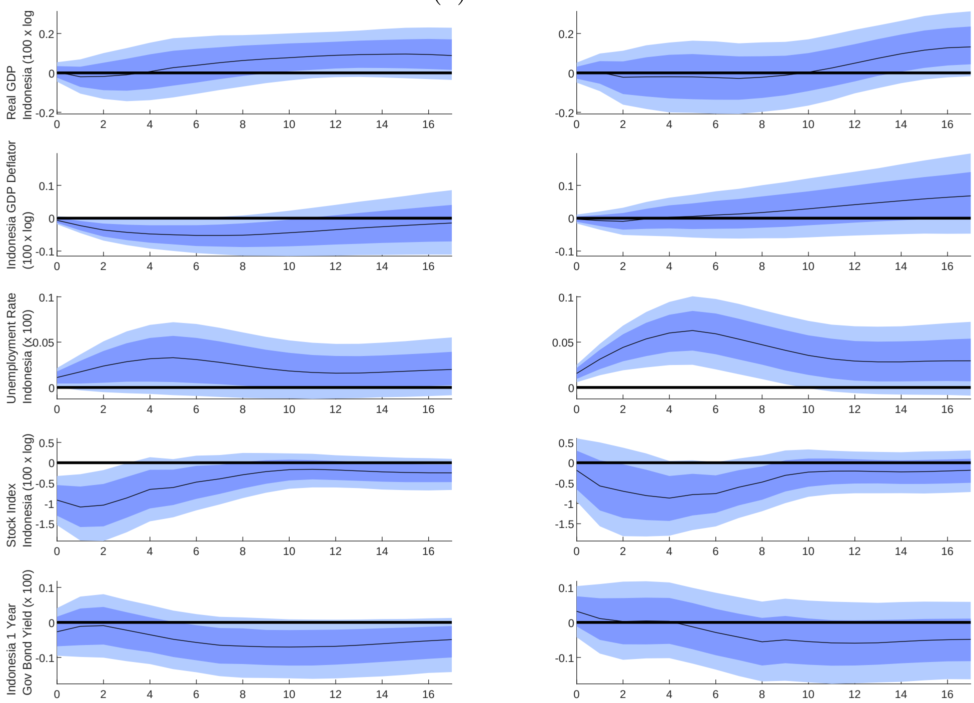
Note: All values are in basis points. Posterior medians and 5th, 95th percentiles. MP = Monetary Policy shock, CB = Central Bank information shock.

The empirical analysis encompassing Russia, Korea, India, Turkey, South Africa, and Indonesia uncovers substantial cross-country heterogeneity in the transmission of FED monetary policy spillovers. This heterogeneity is attributable to the interaction between each country's unique structural attributes and prevailing external conditions. Both MP and CB shocks exhibit heterogeneous effects across these economies, influenced by variations in macroeconomic frameworks, financial market structures, and institutional credibility.

MP shocks generally conform to conventional macroeconomic theory, exerting contractionary effects on output, reducing equity prices, and elevating interest rates. These responses are consistent with the theoretical expectation that tighter monetary conditions suppress economic activity, increase borrowing costs, and curtail investor risk appetite. In contrast, CB shocks manifest more intricate effects, often indicative of central banks' signaling regarding economic fundamentals. These shocks introduce additional layers of complexity, with their impacts varying in both direction and persistence contingent upon market interpretations of the central bank's conveyed information.

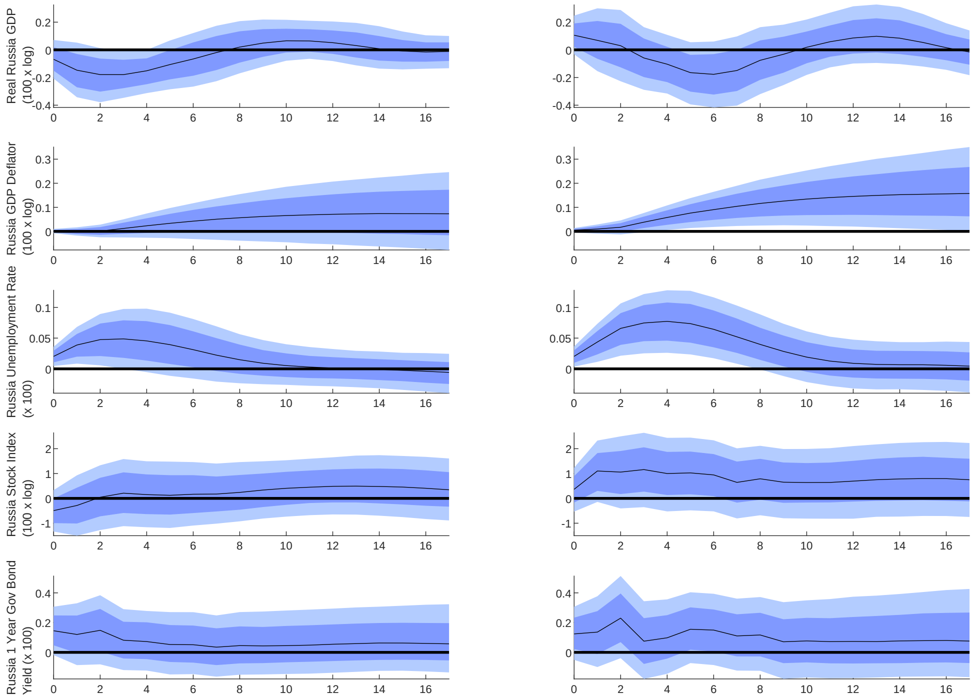


(a) India

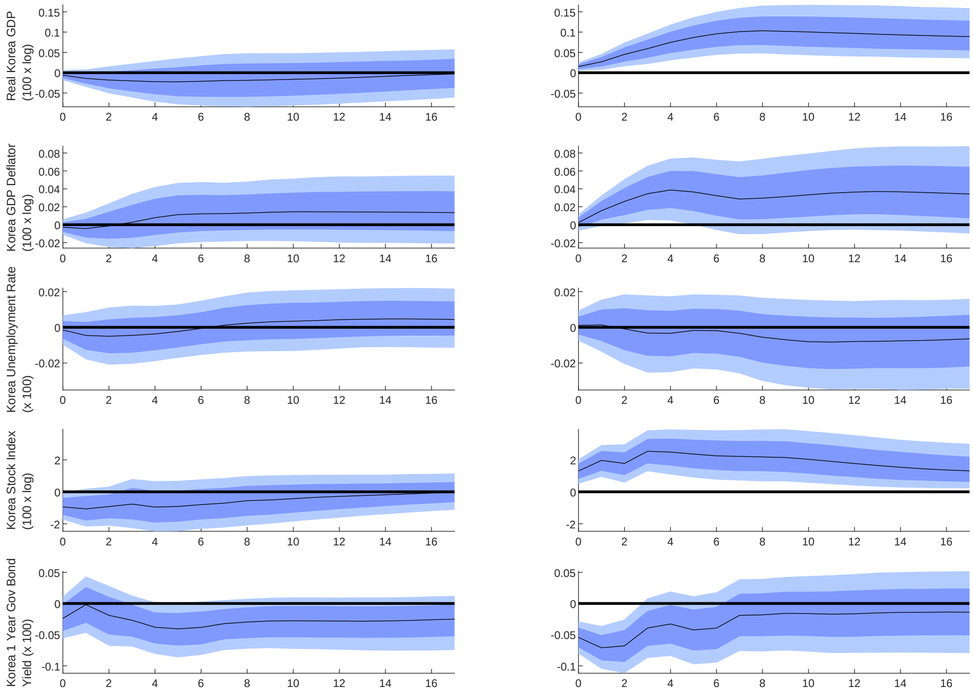


(b) Indonesia

Figure 7: Impulse responses to one standard deviation shocks for multiple countries. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band).

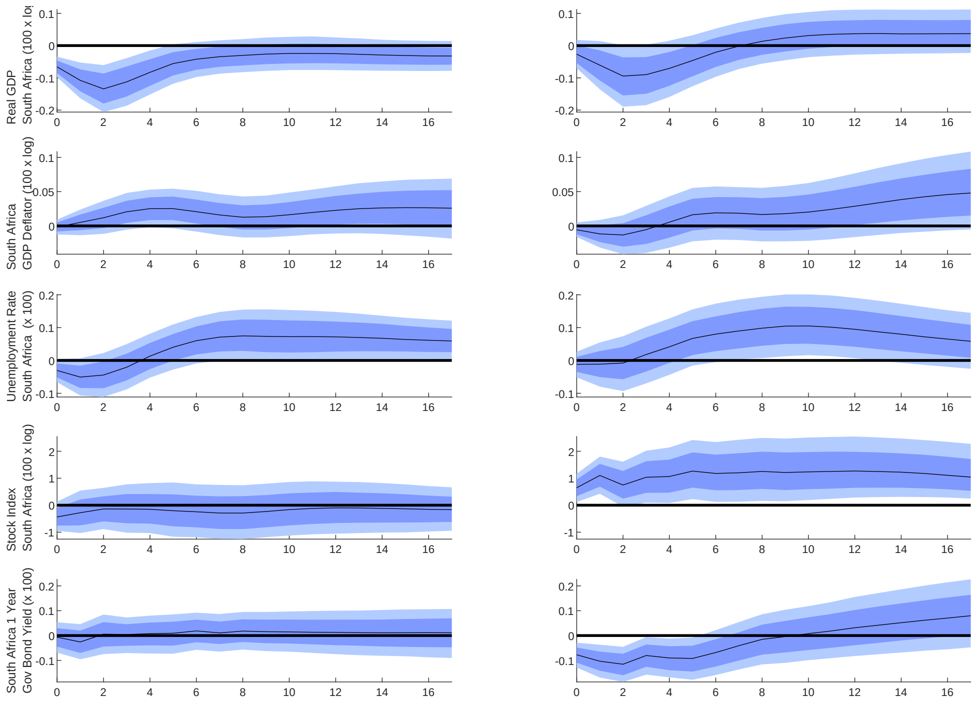


(a) Russia

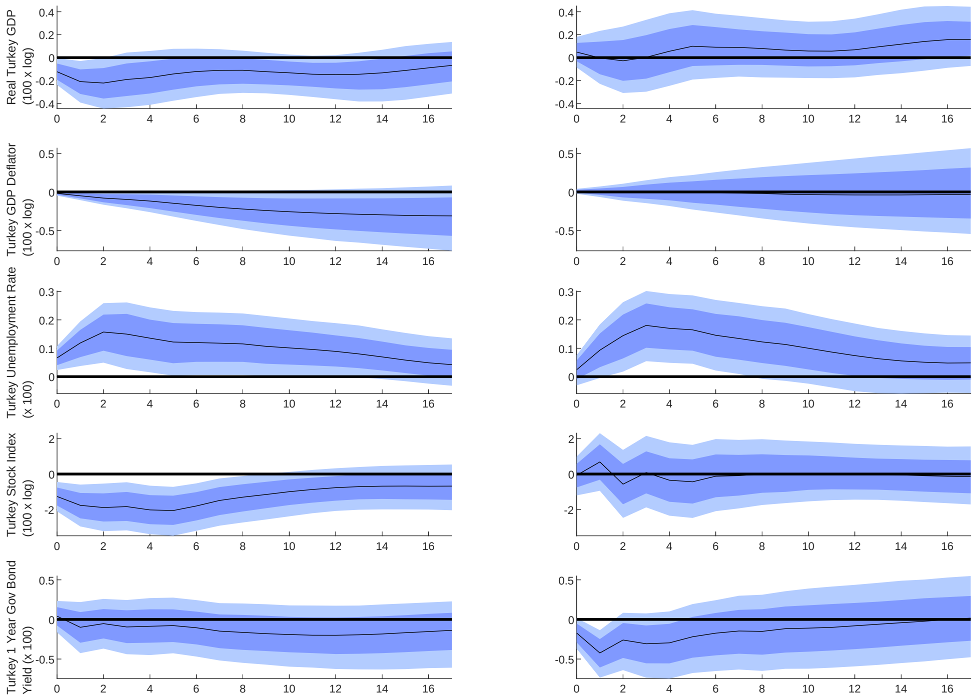


(b) Korea

Figure 8: Impulse responses to one standard deviation shocks for multiple countries. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band).



(a) South Africa



(b) Turkey

Figure 9: Impulse responses to one standard deviation shocks for multiple countries. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band).

In the case of Russia, MP shocks induce contractions in GDP and equity markets, alongside rising government bond yields, which signify tighter financial conditions. Conversely, CB shocks elicit significant positive responses in GDP and equity prices, reflecting an optimistic economic outlook. This divergence underscores the role of CB shocks in signaling favorable future fundamentals, albeit accompanied by increased uncertainty in bond yields. Korea exhibits more subdued reactions, with MP shocks inducing slight GDP contractions and CB shocks producing marginally positive effects on economic activity and equity markets. The muted responses in Korea suggest enhanced macroeconomic stability and robust institutional frameworks that mitigate the impact of external monetary shocks. Additionally, the equity market's lower sensitivity to CB shocks in Korea compared to Russia indicates a reduced responsiveness of financial markets to central bank signaling.

India and Turkey demonstrate pronounced sensitivities to MP shocks, characterized by sharp GDP contractions and significant declines in equity prices, highlighting the vulnerability of these economies to external monetary tightening. Notably, CB shocks in India result in unexpected GDP contractions, potentially signaling market skepticism or apprehension regarding the central bank's informational signaling. In contrast, CB shocks in Turkey appear to attenuate the contractionary effects of MP shocks, thereby playing a stabilizing role. Nonetheless, both countries consistently exhibit negative equity responses to MP shocks, while CB shocks yield mixed outcomes contingent on the nature of the transmitted information.

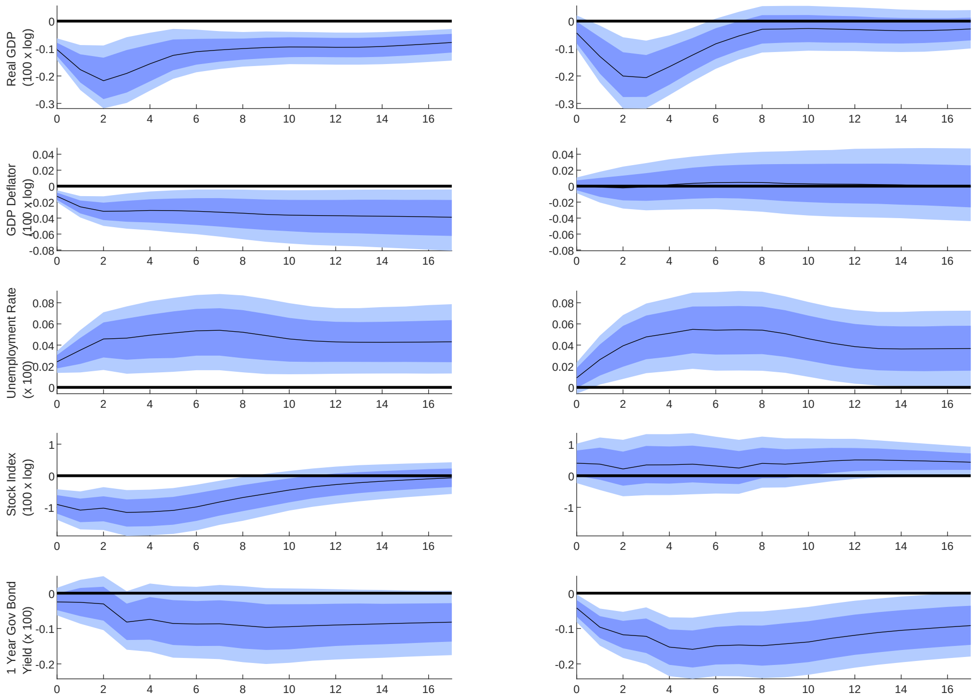
South Africa and Indonesia present distinct transmission dynamics. In South Africa, MP shocks lead to declines in GDP and equity prices, aligning with the tightening of financial conditions. However, CB shocks moderately alleviate these adverse effects, suggesting that central bank communication imparts stabilizing signals. The bond yield responses to CB shocks in South Africa further emphasize the influence of structural and institutional factors on financial market adjustments. Conversely, in Indonesia, MP shocks result in modest GDP contractions, whereas CB shocks are more contractionary, possibly reflecting heightened market uncertainty regarding central bank communications. Additionally, equity markets in Indonesia respond negatively to CB shocks, with bond yield reactions underscoring the complexities inherent in the monetary transmission mechanism within this context.

Overall, the transmission of MP and CB shocks is profoundly contingent on domestic factors, including financial integration, exchange rate regimes, macroeconomic stability, and policy credibility. While MP shocks consistently engender tighter economic and financial conditions, CB shocks introduce greater variability, with their effects contingent upon the nature of the conveyed information and its interpretation by market participants. For instance, CB shocks that signal improved economic fundamentals can mitigate some contractionary effects of MP shocks but may simultaneously engender inflationary pressures or amplify market uncertainty. These findings underscore the paramount importance of country-specific characteristics in shaping the global transmission of FED policies. Emerging market economies, in particular, are highly susceptible to external monetary shocks, underscoring the necessity for tailored domestic policy responses to mitigate adverse spillover effects. The divergent impacts of MP and CB shocks illuminate the dual role of central bank actions in directly influencing monetary conditions and indirectly shaping market expectations through information signaling. A nuanced understanding of these mechanisms is essential for policymakers navigating the complexities of an increasingly interconnected global financial system.

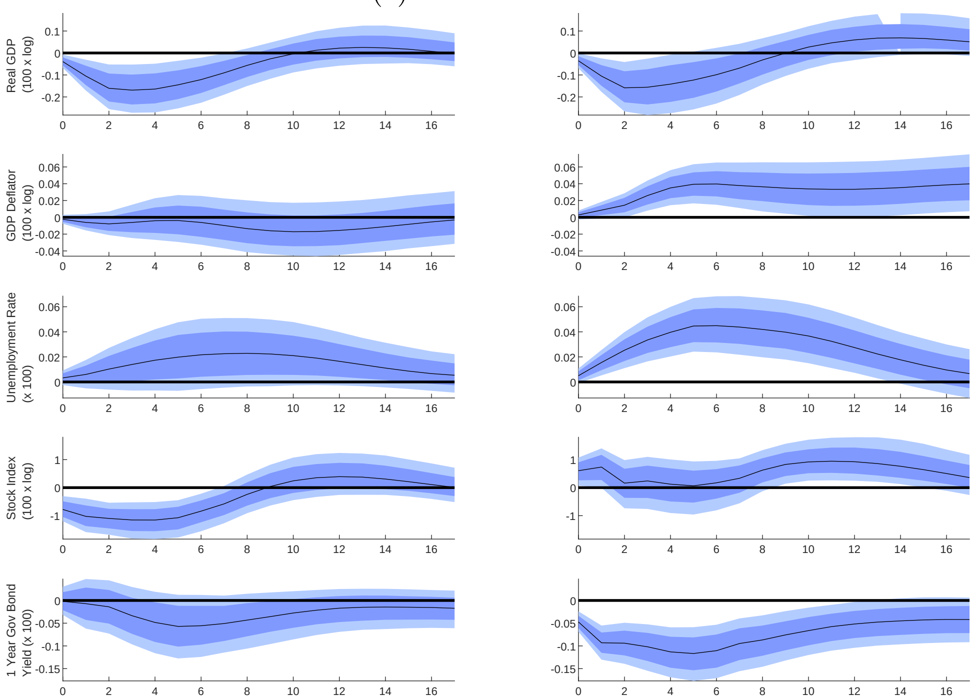
5.2 Regional Impulse Responses

The figures below reports the generalised impulse responses for the two main regions analysed – Latin America and Rest of the world, who are obtained through the stacking of the transmission coefficients, as described in Section 4.

The generalised impulse responses illustrate that U.S. monetary policy tightening generates broadly contractionary spillovers across Emerging Market Economies. Both Latin America and the Rest of the World exhibit declines in real GDP, heightened unemployment, and tighter financial conditions. However, the responses are notably more pronounced and persistent in Latin America, aligning with the region's greater financial vulnerabilities and limited macroeconomic buffers. While initial exchange rate depreciation could theoretically support external competitiveness, the overwhelming influence of financial and balance-sheet channels significantly suppresses real activity and asset prices (as in Rey (2015); Miranda-Agrippino and Rey (2020)). These results align with the established literature, emphasizing that the adverse financial spillovers of external shocks often outweigh trade-related benefits. The findings also underscore the critical role of structural characteristics, institutional quality, and policy frameworks in determining EMEs' resilience to U.S. monetary shocks.



(a) Latin America



(b) Rest of the World

Figure 10: Impulse responses to one standard deviation shocks for multiple countries. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band).

Nevertheless, there are no clear patterns among the Latin American countries. As shown below in Figure 11, the Canova (2007) approach to find convergence groups shows that the highest predictive density is obtained at zero break points (with the Posterior odds ratio even higher in presence of more than one break point).

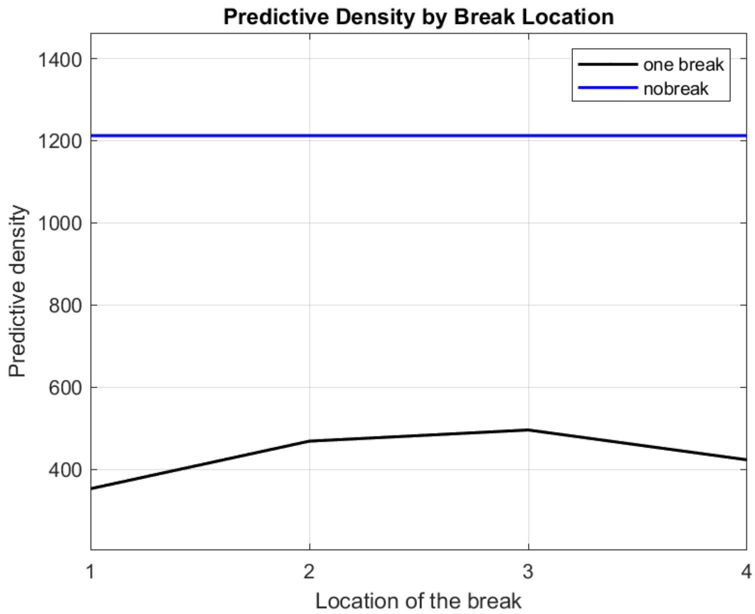


Figure 11: Marginal predictive density as a function of the break point together with the predictive density for zero break points.

6 Conclusion

This study contributes to the ongoing exploration of monetary policy transmission and its global implications, particularly focusing on the differential effects across Emerging Market Economies. By employing high-frequency identification techniques and structural vector autoregressive (SVAR) models in line with Andrade and Ferroni (2016); Jarociński and Karadi (2020); Camara (2021), the current work provides new insights into the heterogeneous responses of key macroeconomic and financial variables to monetary policy shocks. The findings underscore the significant role of both monetary policy shocks and central bank information shocks in shaping economic dynamics, while also highlighting the complex interplay between domestic macro-financial structures and external policy spillovers.

A key takeaway from the analysis is the pronounced heterogeneity in the magnitude and persistence of responses across countries. For instance, monetary policy shocks, characterized by tighter conditions, often lead to notable contractions in GDP, rising unemployment rates, and declining equity prices. In contrast, central bank information shocks reveal a broader range of effects, with some countries experiencing moderate stabilization or even short-term gains depending on the nature of the information conveyed. These results emphasize the dual nature of policy announcements, where market interpretations of central bank signals can either amplify or offset the direct effects of policy rate changes.

The study also confirms that EMEs are particularly vulnerable to U.S. monetary policy spillovers, with their financial systems and macroeconomic conditions frequently magnifying the impacts. Countries with higher levels of financial dollarization, weaker institutional frameworks, or limited exchange rate flexibility tend to experience sharper and more persistent adverse effects. Notably, the contractionary effects of monetary policy shocks are often exacerbated by tighter global financial conditions, while central bank information shocks tend to exhibit more varied and context-dependent impacts. Additionally, no clear pattern emerges from the endogenous grouping methodology (Canova, 2007) applied to the Latin American regional sub-sample, strengthening the conclusion that country-specific characteristics matter.

In conclusion, this research deepens the understanding of monetary policy's global spillovers by bridging the gap between high-frequency financial market responses and broader macroeconomic outcomes. By shedding light on the heterogeneity and complexity of these effects, the study not only advances academic discourse but also provides actionable insights for policymakers navigating the challenges of a globally interconnected economic environment. Future research could extend this analysis by exploring additional dimensions such as the role of unconventional monetary policies, time-varying weight matrix in the stacking of the transmission coefficients, and including other countries in the panel.

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A Data sources

The following data sources have been employed in the current study:

- Dates and times of FOMC announcements are retrieved from Bloomberg. $FF1$, $FF2$, $FF4$ (Fed Funds futures) are obtained from Datascope Tick History, while $ED2$, $ED3$, $ED4$ (Eurodollar futures) from both TickData and Datascope Tick History. S&P500 stock index data derives from Refinitiv.

- GDP, GDP Deflator, and unemployment quarterly data are obtained from Refinitiv, while country major index and 1 year government yield monthly data are retrieved from Investing.com.

B FOMC Announcements

Table 8: FOMC Rate Decisions and Related Announcements

Date/Time	Event
2008-01-22 08:20:00	FOMC Rate Decision (Unscheduled)
2008-01-30 14:15:00	FOMC Rate Decision (Scheduled)
2008-03-11 08:30:00	FOMC statement: Federal Reserve and other central banks announce specific measures designed to address liquidity pressures in funding markets
2008-03-18 14:15:00	FOMC Rate Decision (Scheduled)
2008-04-30 14:15:00	FOMC Rate Decision (Scheduled)
2008-06-25 14:15:00	FOMC Rate Decision (Scheduled)
2008-08-05 14:15:00	FOMC Rate Decision (Scheduled)
2008-09-16 14:15:00	FOMC Rate Decision (Scheduled)
2008-10-08 07:00:00	FOMC Rate Decision (Unscheduled)
2008-10-29 14:17:00	FOMC Rate Decision (Scheduled)
2008-11-25 08:15:00	Federal Reserve announces it will initiate a program to purchase the direct obligations of housing-related government-sponsored enterprises and mortgage-backed securities backed by Fannie Mae, Freddie Mac, and Ginnie Mae. Federal Reserve announces the creation of the Term Asset-Backed Securities Loan Facility (TALF)
2008-12-16 14:15:00	FOMC Rate Decision (Scheduled)
2009-01-28 14:15:00	FOMC Rate Decision (Scheduled)
2009-03-18 14:15:00	FOMC Rate Decision (Scheduled)
2009-04-29 14:15:00	FOMC Rate Decision (Scheduled)
2009-06-24 14:15:00	FOMC Rate Decision (Scheduled)
2009-08-12 14:15:00	FOMC Rate Decision (Scheduled)
2009-09-23 14:15:00	FOMC Rate Decision (Scheduled)
2009-11-04 14:15:00	FOMC Rate Decision (Scheduled)
2009-12-16 14:15:00	FOMC Rate Decision (Scheduled)

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Date/Time	Event
2010-01-27 14:15:00	FOMC Rate Decision (Scheduled)
2010-03-16 14:15:00	FOMC Rate Decision (Scheduled)
2010-04-28 14:15:00	FOMC Rate Decision (Scheduled)
2010-06-23 14:15:00	FOMC Rate Decision (Scheduled)
2010-08-10 14:15:00	FOMC Rate Decision (Scheduled)
2010-09-21 14:15:00	FOMC Rate Decision (Scheduled)
2010-11-03 14:15:00	FOMC Rate Decision (Scheduled)
2010-12-14 14:15:00	FOMC Rate Decision (Scheduled)
2011-01-26 14:15:00	FOMC Rate Decision (Scheduled)
2011-03-15 14:15:00	FOMC Rate Decision (Scheduled)
2011-04-27 12:30:00	FOMC Rate Decision (Scheduled)
2011-06-22 12:30:00	FOMC Rate Decision (Scheduled)
2011-08-09 14:15:00	FOMC Rate Decision (Scheduled)
2011-09-21 14:15:00	FOMC Rate Decision (Scheduled)
2011-11-02 12:30:00	FOMC Rate Decision (Scheduled)
2011-12-13 14:15:00	FOMC Rate Decision (Scheduled)
2012-01-25 12:30:00	FOMC Rate Decision (Scheduled)
2012-03-13 14:15:00	FOMC Rate Decision (Scheduled)
2012-04-25 12:30:00	FOMC Rate Decision (Scheduled)
2012-06-20 12:30:00	FOMC Rate Decision (Scheduled)
2012-08-01 14:15:00	FOMC Rate Decision (Scheduled)
2012-09-13 12:30:00	FOMC Rate Decision (Scheduled)
2012-10-24 14:15:00	FOMC Rate Decision (Scheduled)
2012-12-12 12:30:00	FOMC Rate Decision (Scheduled)
2013-01-30 14:15:00	FOMC Rate Decision (Scheduled)
2013-03-20 14:00:00	FOMC Rate Decision (Scheduled)
2013-05-01 14:00:00	FOMC Rate Decision (Scheduled)
2013-06-19 14:00:00	FOMC Rate Decision (Scheduled)
2013-07-31 14:00:00	FOMC Rate Decision (Scheduled)

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Date/Time	Event
2013-09-18 14:00:00	FOMC Rate Decision (Scheduled)
2013-10-30 14:00:00	FOMC Rate Decision (Scheduled)
2013-12-18 14:00:00	FOMC Rate Decision (Scheduled)
2014-01-29 14:00:00	FOMC Rate Decision (Scheduled)
2014-03-19 14:00:00	FOMC Rate Decision (Scheduled)
2014-04-30 14:00:00	FOMC Rate Decision (Scheduled)
2014-06-18 14:00:00	FOMC Rate Decision (Scheduled)
2014-07-30 14:00:00	FOMC Rate Decision (Scheduled)
2014-09-17 14:00:00	FOMC Rate Decision (Scheduled)
2014-10-29 14:00:00	FOMC Rate Decision (Scheduled)
2014-12-17 14:00:00	FOMC Rate Decision (Scheduled)
2015-01-28 14:00:00	FOMC Rate Decision (Scheduled)
2015-03-18 14:00:00	FOMC Rate Decision (Scheduled)
2015-04-29 14:00:00	FOMC Rate Decision (Scheduled)
2015-06-17 14:00:00	FOMC Rate Decision (Scheduled)
2015-07-29 14:00:00	FOMC Rate Decision (Scheduled)
2015-09-17 14:00:00	FOMC Rate Decision (Scheduled)
2015-10-28 14:00:00	FOMC Rate Decision (Scheduled)
2015-12-16 14:00:00	FOMC Rate Decision (Scheduled)
2016-01-27 14:00:00	FOMC Rate Decision (Scheduled)
2016-03-16 14:00:00	FOMC Rate Decision (Scheduled)
2016-04-27 14:00:00	FOMC Rate Decision (Scheduled)
2016-06-15 14:00:00	FOMC Rate Decision (Scheduled)
2016-07-27 14:00:00	FOMC Rate Decision (Scheduled)
2016-09-21 14:00:00	FOMC Rate Decision (Scheduled)
2016-11-02 14:00:00	FOMC Rate Decision (Scheduled)
2016-12-14 14:00:00	FOMC Rate Decision (Scheduled)
2017-02-01 14:00:00	FOMC Rate Decision (Scheduled)
2017-03-15 14:00:00	FOMC Rate Decision (Scheduled)

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Date/Time	**Event**
2017-05-03 14:00:00	FOMC Rate Decision (Scheduled)
2017-06-14 14:00:00	FOMC Rate Decision (Scheduled)
2017-07-26 14:00:00	FOMC Rate Decision (Scheduled)
2017-09-20 14:00:00	FOMC Rate Decision (Scheduled)
2017-11-01 14:00:00	FOMC Rate Decision (Scheduled)
2017-12-13 14:00:00	FOMC Rate Decision (Scheduled)
2018-01-31 14:00:00	FOMC Rate Decision (Scheduled)
2018-03-21 14:00:00	FOMC Rate Decision (Scheduled)
2018-05-02 14:00:00	FOMC Rate Decision (Scheduled)
2018-06-13 14:00:00	FOMC Rate Decision (Scheduled)
2018-08-01 14:00:00	FOMC Rate Decision (Scheduled)
2018-09-26 14:00:00	FOMC Rate Decision (Scheduled)
2018-11-08 14:00:00	FOMC Rate Decision (Scheduled)
2018-12-19 14:00:00	FOMC Rate Decision (Scheduled)
2019-01-30 14:00:00	FOMC Rate Decision (Scheduled)
2019-03-20 14:00:00	FOMC Rate Decision (Scheduled)
2019-05-01 14:00:00	FOMC Rate Decision (Scheduled)
2019-06-19 14:00:00	FOMC Rate Decision (Scheduled)
2019-07-31 14:00:00	FOMC Rate Decision (Scheduled)
2019-09-18 14:00:00	FOMC Rate Decision (Scheduled)
2019-10-11 11:00:00	Statement Regarding Monetary Policy Implementation (Addressed recent liquidity strains in the repo market by announcing Treasury bill purchases and repo operations)
2019-10-30 14:00:00	FOMC Rate Decision (Scheduled)
2019-12-11 14:00:00	FOMC Rate Decision (Scheduled)
2020-01-29 14:00:00	FOMC Rate Decision (Scheduled)
2020-03-03 10:00:00	FOMC Rate Decision (Scheduled)
2020-03-15 17:00:00	FOMC Rate Decision (Unscheduled)

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Date/Time	Event
2020-04-29 14:00:00	FOMC Rate Decision (Scheduled)
2020-06-10 14:00:00	FOMC Rate Decision (Scheduled)
2020-07-29 14:00:00	FOMC Rate Decision (Scheduled)
2020-09-16 14:00:00	FOMC Rate Decision (Scheduled)
2020-11-05 14:00:00	FOMC Rate Decision (Scheduled)
2020-12-16 14:00:00	FOMC Rate Decision (Scheduled)
2021-01-27 14:00:00	FOMC Rate Decision (Scheduled)
2021-03-17 14:00:00	FOMC Rate Decision (Scheduled)
2021-04-28 14:00:00	FOMC Rate Decision (Scheduled)
2021-06-16 14:00:00	FOMC Rate Decision (Scheduled)
2021-07-28 14:00:00	FOMC Rate Decision (Scheduled)
2021-09-22 14:00:00	FOMC Rate Decision (Scheduled)
2021-11-03 14:00:00	FOMC Rate Decision (Scheduled)
2021-12-15 14:00:00	FOMC Rate Decision (Scheduled)
2022-01-26 14:00:00	FOMC Rate Decision (Scheduled)
2022-03-16 14:00:00	FOMC Rate Decision (Scheduled)
2022-05-04 14:00:00	FOMC Rate Decision (Scheduled)
2022-06-13 15:15:00	WSJ article: Bad Inflation Reports Raise Odds of Surprise 0.75-Percentage-Point Rate Rise This Week (event highlighted by Kurt Lunsford)
2022-06-15 14:00:00	FOMC Rate Decision (Scheduled)
2022-07-27 14:00:00	FOMC Rate Decision (Scheduled)
2022-09-21 14:00:00	FOMC Rate Decision (Scheduled)
2022-11-02 14:00:00	FOMC Rate Decision (Scheduled)
2022-12-14 14:00:00	FOMC Rate Decision (Scheduled)
2023-02-01 14:00:00	FOMC Rate Decision (Scheduled)
2023-03-22 14:00:00	FOMC Rate Decision (Scheduled)
2023-05-03 14:00:00	FOMC Rate Decision (Scheduled)
2023-06-14 14:00:00	FOMC Rate Decision (Scheduled)

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Date/Time	**Event**
2023-07-26 14:00:00	FOMC Rate Decision (Scheduled)
2023-09-20 14:00:00	FOMC Rate Decision (Scheduled)
2023-11-01 14:00:00	FOMC Rate Decision (Scheduled)
2023-12-13 14:00:00	FOMC Rate Decision (Scheduled)
2024-01-31 14:00:00	FOMC Rate Decision (Scheduled)
2024-03-20 14:00:00	FOMC Rate Decision (Scheduled)
2024-05-01 14:00:00	FOMC Rate Decision (Scheduled)

C Minnesota Prior

The Minnesota (Litterman) prior is a specific case of a normal prior where $\bar{\beta}$ and Σ_β depend on a few parameters. We assume $\bar{\beta} = 0$ except for $\bar{\beta}_{i1} = 1$, $i = 1, \ldots, M$, and Σ_β is diagonal. The element $\sigma_{ij,\ell}$ of Σ_β for lag ℓ of variable j in equation i is defined as:

$$\sigma_{ij,\ell} = \begin{cases} \frac{\lambda_0}{h(\ell)} & \text{if } i = j, \forall \ell, \\ \frac{\lambda_0}{h(\ell)} \cdot \lambda_1 \left(\frac{\sigma_i}{\sigma_j}\right)^2 & \text{if } i \neq j, \ j \text{ endogenous}, \forall \ell, \\ \lambda_0 \cdot \lambda_2 & \text{for } j \text{ exogenous}. \end{cases} \tag{20}$$

Here, $\lambda_i \, (i = 0, 1, 2)$ are hyperparameters, $\left(\frac{\sigma_i}{\sigma_j}\right)^2$ is a scaling factor, and $h(\ell)$ is a deterministic function of lag ℓ. The prior captures key features: λ_0 reflects the tightness on the first lag, λ_1 the tightness of other variables, and λ_2 the tightness for exogenous variables.

The function $h(\ell)$ represents the relative tightness of higher lags, typically chosen as a harmonic decay $h(\ell) = \ell^\lambda$ or geometric decay $h(\ell) = \lambda_3^{-\ell+1}$. Since σ_i are unknown, consistent estimates are used.

This prior assumes M time series follow univariate random walks, commonly effective for macroeconomic forecasting. It emphasizes that recent lags provide more information than earlier ones, as $\text{Var}(\ell_2) < \text{Var}(\ell_1)$ for $\ell_2 > \ell_1$. Moreover, the variance of other variables' lags is usually less informative, implying $\lambda_1 \leq 1$. If $\lambda_1 = 0$, the VAR is effectively a random walk.

Finally, λ_2 determines the relative importance of the constants' information, while λ_0 balances the weight between sample and prior information.

If λ_0 is large, the prior becomes diffuse, making the posterior distribution closely reflect the sample information. Conversely, when λ_0 is small, prior information dominates the posterior distribution.