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Fundamental Drivers of Financial Conditions

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Fundamental Drivers of Financial Conditions*

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Resumen

Proponemos un marco estructural para identificar las fuerzas clave que determinan los precios de los activos globales y las condiciones financieras. Nuestro enfoque identifica siete shocks distintos: cuatro centrados en Estados Unidos (crecimiento, política monetaria, prima de riesgo común y un novedoso shock de riesgo de cobertura en dólares), junto con una prima de riesgo global asociada a cobertura, un shock de crecimiento de China y un shock de prima de riesgo específico de los mercados emergentes. Utilizando datos financieros diarios para el período 2010–2025, estimamos un VAR estructural para analizar cómo estos shocks se transmiten entre economías avanzadas y emergentes. Nuestras contribuciones son tres. Primero, introducimos una herramienta de monitoreo en tiempo real que proporciona interpretación estructural y análisis de escenarios, entregando a los responsables de política un marco unificado para evaluar la dinámica de los precios de los activos. Segundo, mejoramos la identificación de los shocks mediante tres innovaciones: (i) incorporamos el shock de riesgo de cobertura en dólares para explicar anomalías observadas desde 2025; (ii) mejoramos la identificación de los shocks de Estados Unidos aprovechando información de activos no estadounidenses; y (iii) destacamos el papel clave de los shocks de crecimiento de China en la configuración de las condiciones financieras de los mercados emergentes. Finalmente, desarrollamos un nuevo Índice de Condiciones Financieras (ICF) basado en shocks estructurales, que permite evaluaciones específicas por país y mejora la interpretabilidad. A diferencia de los ICF tradicionales, nuestro índice vincula directamente las condiciones financieras con sus determinantes económicos, mejora el monitoreo en tiempo real y supera a las alternativas existentes en la capacidad de nowcasting de la actividad económica.

Abstract

We propose a structural framework to uncover the key forces shaping global asset prices and financial conditions. Our approach identifies seven distinct shocks: four U.S.-centric (growth, monetary policy, common risk premium, and a novel dollar-hedging risk), alongside a global hedging risk premium, a China-growth shock and an emerging market-specific risk premium shock. Using daily financial data from 2010–2025, we estimate a Structural VAR to trace how these shocks propagate across advanced and emerging economies. Our contributions are threefold. First, we introduce a real-time monitoring tool that provides structural interpretation and scenario analysis, equipping policymakers with a unified lens to assess asset price dynamics. Second, we improve shock identification through three innovations: (i) incorporating the dollar-hedging risk shock to explain anomalies observed since 2025, (ii) improving U.S. shock identification by leveraging non-U.S. data, and (iii) highlighting the pivotal role of China-growth shocks in shaping emerging-market conditions. Finally, we develop a novel Financial Conditions Index (FCI) grounded in structural shocks, enabling country-specific assessments and enhancing interpretability. Unlike traditional FCIs, our index directly links financial conditions to their economic drivers, improving real-time monitoring and outperforming existing alternatives in nowcasting economic activity.

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1. Introduction

Financial conditions are a cornerstone of monetary policy, offering real-time insights into agents' expectations regarding growth, inflation, and policy direction. They also capture shifts in market sentiment that can independently shape future macroeconomic dynamics. Although these conditions manifest through asset prices, the forces driving them are not directly observable. Crucially, uncovering these drivers is essential, as similar movements in asset prices may stem from fundamentally different shocks–be it monetary policy changes, evolving growth outlooks, or shifts in risk appetite–each with distinct implications for macroeconomic outcomes and appropriate policy responses.

Building on Cieslak and Pang (2021) we develop a strategy to identify the fundamental drivers of global asset prices. In our baseline model, these include short and long-term yields, stock market returns, and exchange rates for the U.S. and a block of emerging markets. We identify seven structural shocks, four US centered (US growth, US monetary policy, U.S common risk premium, and a new *dollar-hedging risk*) and three global, which we label as, *global hedging risk-premium*, *China growth* and *emerging-markets'-specific risk-premium* shock. A larger version of the model, which we use as a robustness check, also includes long-term yields, stock market returns, and exchange rates of a block of developed economies, together with oil and copper prices.

Using the estimated shocks, we: (i) Analyze their influence on major global financial episodes and trace their international transmission, providing indirect validation to our estimations by comparing our decompositions with established narratives. (ii) Introduce a new structurally interpretable financial conditions index (FCI) customizable for any economy or country group, which complements traditional metrics. Unlike other available FCIs–which typically rely on weighted averages of financial variables—this structural approach offers structural interpretability and enables scenario-based policy simulations.

Asset price movements are equilibrium outcomes that reflect a mix of structural drivers, making it difficult to disentangle the underlying shocks from prices alone. However, understanding these drivers is crucial for monetary policy, as appropriate policy responses depends heavily on the nature of the shock. Much as the optimal reaction to rising inflation varies depending on whether it stems from demand or supply factors, so too shifts in financial conditions carry different implications depending on their origin. For example, an increase in long-term interest rates in an emerging market could signal either stronger growth expectations or heightened risk aversion, each requiring a distinct policy interpretation, and potentially affecting monetary policy decisions of a central bank that seeks to affect, or even target, local financial conditions (for an argument of why central banks should target financial conditions, see Caballero et al., 2024).

We make three main contributions. First, we introduce a tool for real-time monitoring of global asset prices, providing a structural interpretation within a unified framework that enables scenario analysis. Second, our approach enhances the identification of shocks–including those originating in the U.S.–through three innovations: (i) it highlights the critical role of Dollar-Hedging Risk in understanding the events since 2025; (ii) it shows that using non-U.S. assets to identify U.S.

shocks improves the accuracy of shock identification; (iii) it highlights the crucial importance of the China growth shock to understand emerging markets' asset prices dynamics. Finally, we propose a Financial Conditions Index that not only offers structural interpretability, but also outperforms other available alternatives in nowcasting economic activity.

The empirical findings reveal that U.S. monetary policy and common risk–premium shocks generate significant spillovers to emerging markets, notably impacting long-term yields and exchange rates. The China–growth shock accounts for nearly 30% of the variance in emerging-market exchange rates, underscoring its central role in shaping their financial conditions, while the emerging-markets–specific risk–premium shock explains more than 50% of the variance in their equity indices. In addition, the results show that U.S. growth shocks substantially influence U.S. equity markets—explaining nearly half of their variance—although their global spillovers are more modest, and that global hedging (risk-on/risk-off) shocks meaningfully drive both U.S. and EME yields, consistent with flight-to-safety dynamics.

The newly introduced dollar-hedging risk shock captures key anomalies observed in 2025, such as the depreciation of the dollar occurring alongside rising long-term yields and falling equity prices—patterns that traditional two-factor risk-premium models fail to account for. Event studies confirm the model's ability to interpret asset-price dynamics during major episodes like the Taper Tantrum, the 2011 Euro-area debt crisis, and the 2024 Jackson Hole meeting. Finally, the structurally interpretable Financial Conditions Index derived from these shocks outperforms available alternatives in nowcasting economic activity, mainly by distinguishing between the fundamental causes of shifts in financial conditions.

The paper is organized as follows. Section 2 reviews related literature. Section 3 presents the methodological framework, detailing the estimation strategy, the algorithm employed, and the data sources. Section 4 outlines the identification strategy. Section 5 includes an event study aimed at deepening the understanding of the proposed shocks. Section 6 reports more detailed empirical results. Section 7 includes robustness checks. Section 8 introduces our proposed Financial Conditions Index and estimates it for the US, and section 9 estimates it for some selected emerging economies. Section 10 concludes.

2. Related Literature

This paper connects with three main areas of literature: the identification of structural shocks in high frequency through asset prices, the measurement of global financial spillovers to emerging markets, and the construction of financial conditions indices.

The identification of structural shocks through high frequency financial data has evolved substantially in recent years, with the main applications related to identification of exogenous monetary and risk shocks from daily or intraday asset price movements. High-frequency methods exploit the information content embedded in financial markets, enabling a more precise distinction between policy actions, information effects, and shifts in risk sentiment. The narrow-window approach, typically a 30-minute window around official announcements, assumes that within such a short interval, policy communication is the only exogenous event affecting asset prices (Gürkaynak et al., 2005; Nakamura and Steinsson, 2018; Andrade and Ferroni, 2021). This framework, rooted in the early work of Kuttner (2001) and expanded by Gürkaynak et al. (2005), decomposes rate surprises into a "target factor" and a "path factor" reflecting forward guidance. More recent studies highlight that even high-frequency policy surprises can contain information about fundamentals, the so-called "Fed information effect." To isolate the pure monetary component, Bauer and Swanson (2023) orthogonalize policy surprises with respect to pre-announcement macroeconomic news. Similarly, Jarociński and Karadi (2020) and Cieslak and Schrimpf (2019) exploit the co-movement between stocks and bonds to distinguish monetary policy shocks, marked by a negative bond–stock co-movement, from central bank information shocks, which exhibits a positive co-movement.

Parallel advances extend these methods to daily-frequency data, enabling the identification of shocks that emerge continuously through market reactions to news, rather than at scheduled announcement. Using daily-frequency SVARs with sign restrictions, Matheson and Stavrev (2014) identified monetary and economic news shocks from the correlation between equity prices and long-term yields. Building on this idea, Lodge and Manu (2022) employed a daily Bayesian SVAR to jointly identify four global shocks – oil supply, global and U.S. economic news, and U.S. monetary policy– demonstrating that meaningful structural shocks can be extracted even outside narrow event windows. Similarly, Cieslak and Pang (2021) analyzed decades of daily data to decompose yield and stock movements into growth, monetary, and risk-premium shocks, showing that economically motivated restrictions can hold consistently at the daily frequency. Overall, this literature underscores how the joint behavior of asset prices across markets and maturities provides a powerful lens for extracting structural shocks from financial data. We build on these insights by implementing a daily SVAR that systematically identifies global shocks across asset classes and regions, combining high-frequency precision with global financial coverage.

A second strand of literature examines how such shocks propagate internationally. A broad empirical consensus finds that changes in U.S. monetary policy generate sizable cross-border effects (Ahmed et al., 2021; Georgiadis, 2016). These spillovers operate through multiple reinforcing channels. The *global financial cycle* and its associated *risk-taking channel* are central: U.S. monetary tightening reduces global risk appetite, triggers deleveraging among global intermediaries, and tightens credit conditions worldwide (Miranda-Agrippino and Rey, 2020; Ahmed et al., 2021). In bond markets, spillovers to emerging-market yields primarily affect term premia and credit-risk components, implying that local financing costs may move independently of domestic fundamentals (Albagli et al., 2019; Solís, 2025). Unconventional monetary policies such as quantitative easing have also transmitted globally through valuation and risk channels, as shown by Chari et al. (2021).

The magnitude of these effects is heterogeneous across economies and depends on the source of the shock. Policy-driven hawkish-tightenings tend to depress activity and tighten financial conditions across EMEs, while growth-driven rate increases can generate milder or even positive effects in more resilient economies (Hoek et al., 2022; Ahmed et al., 2021). Spillovers are further amplified by domestic vulnerabilities such as shallow financial markets, dollarized liabilities, and limited policy credibility, that heighten exposure to global shocks (Georgiadis, 2016). Recent high-frequency studies show that global risk and growth shocks explain a large share of daily fluctuations in EME asset prices, often exceeding the influence of U.S. specific monetary shocks (Lodge and Manu, 2022). Our paper builds directly on this evidence by offering a unified structural decomposition of global shocks that disentangles U.S.-specific and global factors, allowing us to quantify their heterogeneous transmission across economies.

A third body of research focuses on summarizing the stance of financial conditions through composite indicators. Traditional Financial Conditions Indices (FCIs) aggregate information from interest rates, credit spreads, equity valuations, exchange rates, and volatility indicators into a single measure of financial tightness or ease (Dudley and Hatzius, 2000; Dudley et al., 2005). Early FCIs relied on principal component methods or weighted-sum frameworks, capturing common co-movements across financial variables or assigning weights based on their predictive relationship with real activity (Hatzius et al., 2010). These measures provide useful real-time gauges of financial tightness but remain reduced-form constructs that do not disentangle the underlying sources of financial fluctuations.

Subsequent contributions sought to enhance FCIs by allowing for time variation and model flexibility. Notably, Koop and Korobilis (2014) introduced a time-varying parameter FAVAR framework with dynamic model averaging, allowing the relevance of financial variables to evolve over time and improving short-term forecasting performance. Nevertheless, even these approaches remain statistical in nature, summarizing co-movements rather than identifying structural drivers. Our paper contributes to this literature by proposing a shock-based Financial Conditions Index that explicitly decomposes financial fluctuations into structural drivers. This framework bridges reduced-form and structural approaches, directly linking financial conditions to their economic origins. In doing so, it enhances interpretability, supports scenario-based policy analysis, and enables cross-country comparisons of how global shocks shape domestic financial environments. The approach extends the interpretative aims of Hatzius et al. (2010) and the dynamic flexibility of Koop and Korobilis (2014), offering a coherent structural representation of global financial conditions.

3. Methodological framework

The baseline model is a SVAR estimated using standard frequentist techniques. The model is estimated by ordinary least squares (OLS) on the reduced form, with identification achieved through sign restrictions imposed on the impulse response functions (IRFs). These restrictions isolate economically interpretable structural shocks while remaining agnostic about the contemporaneous causal ordering of the variables

The reduced-form VAR can be formally expressed as:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \quad u_t \sim (0, \Sigma_u), \tag{1}$$

where y_t is an $(n \times 1)$ vector of endogenous variables, A_i are autoregressive coefficient matrices, and Σ_u is the covariance matrix of reduced-form residuals.

The structural representation assumes that the reduced-form innovations u_t are linear combinations of n structural shocks ε_t:

$$u_t = B\varepsilon_t, \quad \varepsilon_t \sim (0, I_n), \tag{2}$$

where B is the $(n \times n)$ contemporaneous impact matrix. Because $\Sigma_u = BB'$, identifying B requires additional restrictions. A Cholesky decomposition provides one admissible solution $\tilde{B}$ such that $\Sigma_u = \tilde{B}\tilde{B}'$, but infinitely many alternative solutions exist:

$$B = \tilde{B}Q, \quad QQ' = I_n, \tag{3}$$

where Q is an orthogonal rotation matrix. The set of all possible Q matrices defines the space of admissible structural models consistent with the reduced form.

The identification algorithm follows a standard accept–reject procedure. For each draw, the implied structural impact matrix $B_i = \tilde{B}Q_i$ is used to compute the corresponding impulse responses $\text{IRF}_i(h)$ at horizons $h = 0, 1, \ldots, H$. These responses are then evaluated against the theoretical sign restrictions $\mathcal{S}$ imposed on selected variables :

$$\text{IRF}_i(h) \in \mathcal{S} \quad \forall h \in H. \tag{4}$$

Draws that satisfy all restrictions are accepted, while those that violate any restriction are discarded. The retained set of admissible models $\{B_i\}_{i \in \mathcal{A}}$ is then used to compute median impulse responses, forecast error variance decompositions (FEVDs), and historical decompositions consistent with the imposed economic structure.

As a robustness exercise, we also estimate a high-dimensional Bayesian version of the model following Korobilis (2022), which extends the analysis to a larger set of variables and structural shocks. The Bayesian algorithm employs hierarchical shrinkage priors and a Gibbs sampling procedure that make it computationally efficient for large-scale SVARs, helping to overcome the dimensionality and numerical constraints that typically limit frequentist estimation. This complementary framework confirms the stability of our identification strategy and ensures that the results are not sensitive to the estimation method.

3.1. Data

We use daily financial data from January 2, 2010, to May 30, 2025. The dataset includes variables for the United States, a representative block of emerging market economies (EMEs), and China. The baseline specification comprises seven endogenous variables capturing key financial markets across these regions: the 2-year and 10-year U.S. bond yields ($2y_{US}$, $10y_{US}$), the S&P 500 equity index (Eq_{US}), the 2-year and 10-year sovereign yields factor for EMEs ($2y_{EME}$, $10y_{EME}$), an equity index factor for emerging economies (Eq_{EME}), and an aggregate EME exchange rate index (FX_{EME}). These variables are selected to identify seven structural shocks corresponding to the main sources of global financial variation: U.S. growth, U.S. monetary policy, U.S. common risk premium, U.S. dollar-hedge, Global hedging premium, Chinese growth, and an EME risk premium. All series are expressed in stationary form. Sovereign yields enter the VAR in first differences, while stock market indices, exchange rates, are expressed in log-differences.

To represent the financial block of emerging markets, we aggregate individual country series through principal components (PCs). Specifically, for each asset class – 2-year and 10-year yields, equity factor and exchange rates index–we compute the first principal component across the fifteen emerging economies in our sample.[1] Because principal components are standardized by construction, we re-scale them to ensure comparability with the original series. This is achieved by regressing the median series of each group on the corresponding principal component and using the fitted value as the variable entering the VAR:

$$x_t^* = \hat{\alpha} + \hat{\beta} \cdot PC_t,$$

where x_t^* denotes the fitted value preserving the median unit of measurement. This adjustment ensures that the estimated factor retains the interpretation of a representative series for the block, while preserving the cross-sectional co-movement captured by the PC. The resulting dataset yields a seven-dimensional daily VAR ($n = 7$) that captures the dominant financial interactions between the United States, China, and the emerging market block.

As a robustness exercise, in section 7 we also estimate a larger model that expands the information set to fifteen variables, incorporating additional U.S. and EMEs rates (5-year U.S. yield and 2-year for EMEs), financial indicators for advanced economies (2-year and 10-year, equities, and exchange rates), and prices of oil, and copper. This specification retains the same structural logic as the baseline model–identifying the same seven shocks. Also, we estimate a reduced model with six variables and six shocks.

4. Identification strategy

We adapt and extend Cieslak and Pang (2021) identification strategy to recover seven structural shocks driving global asset prices –four centered on the U.S. and three global–, using a combination of sign and magnitude restrictions. The shocks encompass the four U.S.-centered identified by Cieslak and Pang (2021): A U.S. growth shock, a U.S. monetary policy shock, a common risk-premium shock, and a hedging risk-premium shock. Our identification approach, however, is not the same to that of Cieslak and Pang (2021). We depart from the authors in four primary respects: First, by incorporating a third fundamental source of risk in the U.S.—the *dollar-hedging risk*. Second, by considering global effects in the identification strategy for the U.S shocks. Third, we include a China growth shock aimed at capturing variations in Chinese economic news prospects.

[1] The EME group includes Brazil, Chile, Colombia, Czech Republic, India, Indonesia, Malaysia, Mexico, Poland, Peru, North Korea, Thailand, Hungary, South Africa and Sri lanka.

Fourth, we include a emerging markets risk premium shock to reflect shifts in investor sentiment toward these economies. The remainder of this section is devoted to explaining each shock in more detail.

The **U.S. growth shock** is identified through a positive co-movement between short- and long-term yields and equity prices in the U.S., reflecting improved economic fundamentals that raise both expected returns and interest rates. As in Cieslak and Pang (2021), we impose that the U.S. short-term rate responds more than the long-term rate, highlighting the greater sensitivity of short rates to growth expectations (see column 1 of table 1). Also, we impose that U.S. equity index responds more than EMEs equity index. In the larger version of the model, this shock raises equity prices of emerging markets (EMEs), and leads to local currency appreciation, consistent with Lodge and Manu (2022) findings.

The **global hedging risk-premium shock**, can be thought as a typical *risk-on/risk-off* shock, and also generates a positive co-movement between U.S. yields and equity prices. During *risk-off* episodes, this shock results in a flight-to-safety dynamic, whereby the prices of risky assets decline while those considered safe appreciate (so that U.S. bond yields decrease). Unlike growth shocks, this affects long-term rates more than short-term ones, in line with Cieslak and Pang. We depart form Cieslak and Pang, by also requiring some specific international spillovers for this shock. A *risk-off* shock tends to exert downward pressure on global equity markets and the bond prices of emerging economies on impact.

The **U.S. common risk-premium shock** refers to a change in the discount rate risk premium that affects equity and bond yields in the opposite direction. When the risk premium rises, equity prices decrease and bond yields rise, with yields on long-term bonds increasing more than those on short-term ones. Thus, it can be thought as a preference-for-liquidity shock. As we show in next section, this shock tends to appreciate the U.S. dollar against all currencies, reflecting the higher preference for liquidity. Outside the United States, similar effects are imposed: equity prices decline, bond yields increase and currencies depreciate against the dollar (see column 3 of table 1).

The **U.S. monetary policy shock** is also characterized by a negative co-movement between bond yields and equity prices in the U.S. As opposed to the common risk shock, the short-term yield is restricted to move more strongly than the long-term yield, consistent with the larger effect of monetary policy on short-run rates, same as in Cieslak and Pang identification. Outside the U.S., short and long-term rates rise, equity prices fall, and currencies depreciate, aligning with the international transmission of U.S. monetary policy shocks, largely documented in the literature– e.g., Albagli et al., 2019, 2024 and Lodge and Manu, 2022 (see column 4 of table 1).

The **dollar-hedging risk** introduces a third factor in the U.S. risk-premium structure. It is primarily motivated by the unusual asset prices' dynamics since early 2025, which appear linked to recent U.S. trade policy developments and various institutional and geopolitical events. In early April, amid a significant rise of the VIX, the stock market declined sharply, long-term yields climbed, while the dollar depreciated, in contrast of what the evolution interest rates would have predicted (more details in section 5). These trends continued thought the year beyond the specific events of April, but cannot be well accounted for by the two-factor risk premium proposed by Cieslak and Pang (2021). With stock markets down and long-term bond yields up, the model mostly attributes long-term yield increases to the common premium shock, as we show in section 5. However, after a large common premium shock, an appreciation of the U.S. dollar should have followed, as indicated by the estimated Impulse Response Function of the dollar index (DXY) to Cieslak-Pang's shocks we discuss in section 5. Indeed, in that section we also show that an historical decomposition of the DXY based on IRFs to all the four Cieslak-Pang's shocks indicates that most of the DXY depreciation during 2025 has to be explained by a large residual. Moreover, while the common premium shock typically weakens emerging market currencies, lowers their stock markets, and raises long-term yields, emerging economies' financial markets performed quite well in the first half of 2025.

To address this issue, our proposed **dollar-hedging risk** reflects shifts in investors preferences toward all U.S. assets, not just those typically considered *risky*. In practical terms, this shock generates movements similar to those caused by a common risk-premium shock; but, it leads to a depreciation, rather than appreciation, of the U.S. dollar against all currencies, including EMEs'. Also, we impose that the response of the U.S. equity is larger than the EMEs equity (see column 5 of Table 1).

The **China growth shock** reflects shifts in China's growth outlook, which are known to significantly impact commodity prices and emerging markets' asset prices (see e.g., Gutierrez et al., 2024). A positive China-growth shock raises the emerging markets's equity index and the S&P (though less than the EMEs), and appreciates EMEs currencies and increase their long and short term rates. In the larger version of the model, this shock also increases commodity prices and stock markets of developed economies (see column 6 of Table 1). In next section we show that this shock accounts for a substantial share of the variance in EME asset prices, so that omitting it could lead to erroneous conclusions. Similar to the U.S. growth shock, we impose that the EMEs short-term rate responds more than the long-term rate.

Finally, the **Emerging markets' specific risk premium shock** represents a risk factor specific to emerging markets, intended to capture fluctuations in risk sentiment toward these markets, but not necessarily to other risky assets. Examples include the 1994 *tequila crisis* and the 1997-98 *Asian and Russian crises*. In our sample (Jan 2010–May 2025), the most significant events are the *Greek debt crisis* in September 2011 and the *taper tantrum* in June 2013. While these events impacted all risky assets, their effects on emerging markets were larger than during a typical risk-off event (details are provided in the next subsection). A higher EME risk-premium shock raises yields, lowers equity prices (and more the EMEs than U.S.), and weakens exchange rates in emerging markets. Moreover, this shock–similar to U.S risk-premium shocks– has a stronger effect on long-term yields than on EMEs short-term rates. (see column 7 of table 4).

Table 1 summarizes all the identification restrictions. The direction of the shocks should be interpretes as follows: U.S. and China growth shocks reflect stronger economic growth; the global hedging shock corresponds to a risk-off environment; the U.S. common premium shock signals higher common risk or greater liquidity preference; the U.S. monetary policy shock represents a more contractionary stance; the dollar-hedging shock indicates a lower preference for U.S. assets; and the EME risk shock captures increased risk in emerging markets.

Table 1. Baseline Identification Matrix

		(1)US Growth	(2)Global Hedging	(3)US Common	(4)US MP	(5)Dollar Hedge	(6)China Growth	(7)EMEs Risk
US	2-year	1	-1	1	1	1	NaN	NaN
	10-year	1	-1	1	1	1	NaN	-1
	Equity	1	-1	-1	-1	-1	1	-1
EME	2-year	NaN	NaN	1	1	NaN	1	1
	10-year	NaN	1	1	1	NaN	1	1
	Equity	NaN	-1	-1	-1	NaN	1	-1
	FX	NaN	1	1	1	-1	-1	1

Notes: Sign and magnitude restrictions imposed for structural identification. NaN remain as unrestricted values. The model considers magnitude restrictions between variables for the following shocks. For US Growth: 2y US > 10y US and Equity US > Equity EME; US Hedging Risk: 10y US > 2y US and 10y EME > 2y EME; US Common Risk: 10y US > 2y US; US MP: 2y US > 10y US; Dollar Hedge: Equity US > Equity EME; China Growth: 2y EME > 10y EME and Equity EME > Equity US; EME risk: 10y EME > 2y EME and Equity EME > Equity US.. Finally, we impose intra-variable magnitude restrictions on different shocks. For 2y US: US growth + US MP > US Common Risk + US Hedging Risk; for 10y US, the opposite. These latter intra-variables restrictions are adopted from Cieslak and Pang (2021).

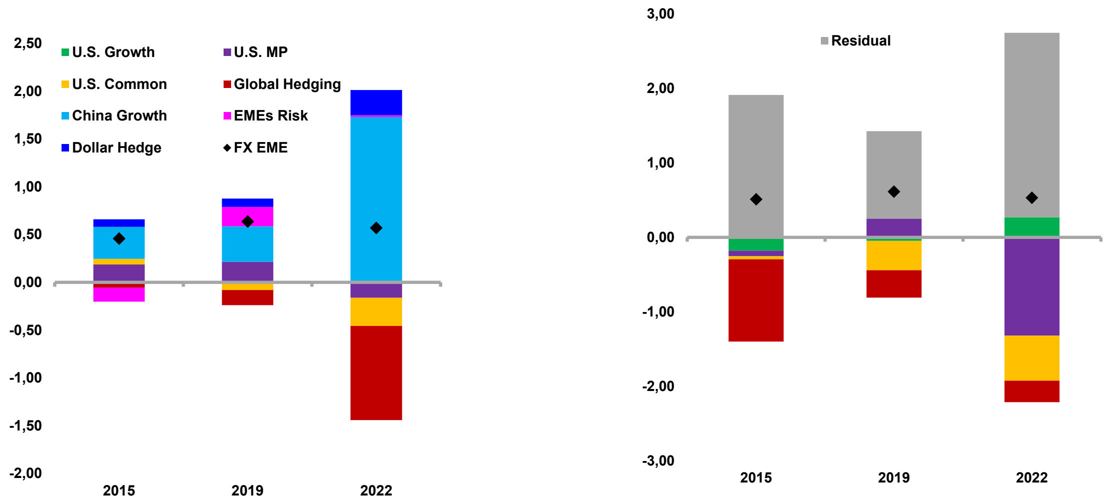
5. Event Studies

In this section we present some event studies to support our identification strategy. It is divided into two parts: the first examines the dynamics of the new shocks introduced in this paper in specific periods, and second analyzes the narratives derived from the historical decompositions of our model around key past events.

5.1. Validation of the the new shocks

In this first part we make special emphasis on analyzing how the new shocks introduced in this paper (i.e., the *China Growth Shock*, the *U.S. Dollar-Hedging Shock*, and the *Emerging Markets Risk Premium Shock*) behave around specific salient events. We also highlight the importance of using non-U.S. data to more accurately shocks typically identified just with U.S. assets.

China Growth Shock. This shock reflects shifts in expectations around Chinese growth outlook. To identify the key episodes likely driven by this shock, we used Google Trends and a Bloomberg tool that tracks keyword frequency in news and search data, filtering specifically for "shock China" and "China growth". The most prominent episodes in our sample (excluding the pandemic) occurred in early 2015, when China's GDP growth fell to 7.4%, signaling the onset of the "new normal" and revealing early signs of stress in the property sector; in 2019, during the intensification of the U.S.–China trade war I, which brought tariff escalations, currency depreciation, and heightened uncertainty that reverberated across global markets; and in mid-2022, when growth weakened again amid renewed COVID restrictions and mounting pressures in the real estate sector. During those episodes, emerging market exchange rates depreciated, consistent with our model's impulse response functions (detailed impulse responses are included in next section). Consistently, our historical decomposition attributes most of EMEs' depreciation to the China growth shock (figure 1a). In contrast, using only Cieslak and Pang's original shocks, the depreciation is mostly assigned to a large residual (figure 1b), suggesting that the newly identified shock captures a key driver of exchange rate movements omitted in standard macro-financial models.



(a) Historical decomposition FX EMEs, Global Model

(b) Historical decomposition FX EMEs, Cieslak and Pang shocks

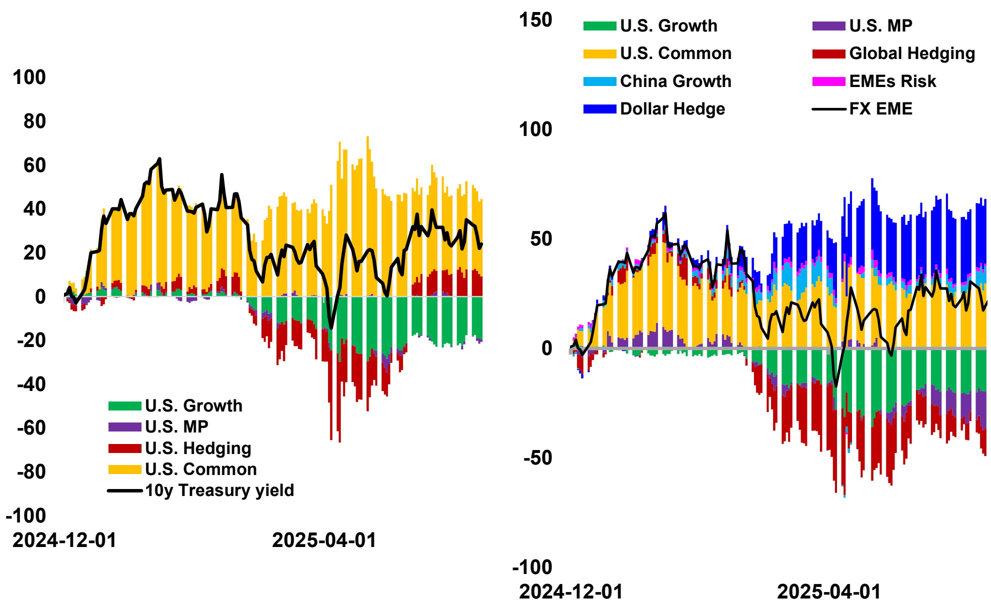
Figure 1. Historical decompositions of EMEs FX on specific *China growth* shocks events

Notes: Cumulated to day 5 since each event. 2015 since 22/12/24; 2019 since 22/07/19; 2022 since 17/06/22. Percentage points.

U.S. Dollar-Hedging Shock. As described above, this shock emerges as a third factor in the U.S. risk premium structure, driven by the unusual asset price movements since early 2025—likely tied to trade policy and geopolitical shifts. In April, stock markets fell, long-term yields rose, and the dollar depreciated—contrary to the evolution that interest rates would have predicted (see figure A.1 of the appendix).

These patterns persisted beyond April but aren't well explained by the two-factor risk premium model from Cieslak and Pang. While that model links rising long-term yields to a common premium shock (figure 2a), an estimated IRF of this shock on the U.S dollar shows that such a shock should have generated a stronger dollar (figure B.1a of the appendix)–which did not happen. Thus, an historical decomposition constructed with all four Cieslak and Pang shocks assigns the dollar depreciation in that period to a large residual (figure B.1b of the appendix). Moreover, in contrast to observed dynamics, emerging markets asset prices should have suffered heavily after a large common premium shock (figure B.1c of the appendix shows the implied IRF of EMEs stock prices to a common premium shock).

As shown in figure 2b, our proposed *dollar-hedging* shock solves all of those issues and accounts a significant portion of asset markets movements during this year.



(a) HD of U.S. 10 year yield using Cieslak and Pang (2021) shocks **(b)** HD of U.S. 10 year yield using shocks from our model

Figure 2. Historical decompositions (HD) of 10y Treasury yield
Notes: Cumulated since December 2024, basis points.

Emerging Markets Risk Premium Shock. This shock captures changes in investor sentiment specific to emerging markets, distinct from general global risk aversion. Periods when this shock spikes coincide with well-documented stress events in EM financial markets. The largest positive realizations are observed in June 2013 –the "taper tantrum"–, May 2010 –the European sovereign debt crisis–, and March 2020–the onset of the COVID-19 crisis– (see figure 3). In all the three cases, EM sovereign yields rose, equity prices fell, and currencies depreciated. These dynamics are consistent with capital outflows from EM assets and flight-to-quality behavior.

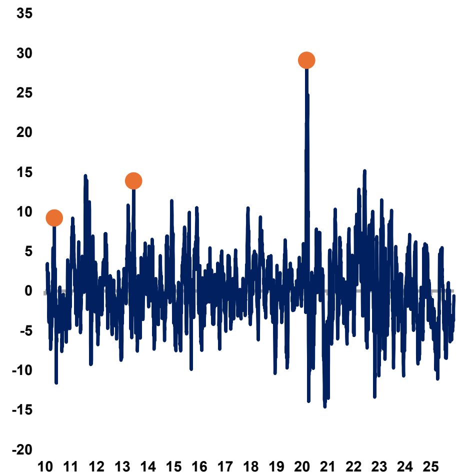
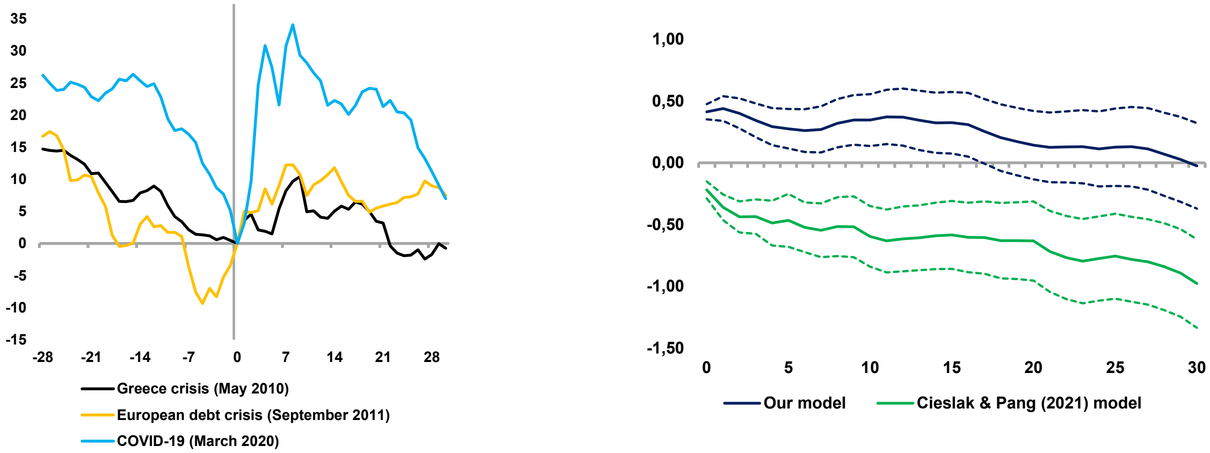


Figure 3. *EME risk* shock time series

Notes: 30-day rolling sum. The dots indicate the events the European sovereign debt crisis (May 2010); the Taper Tantrum (June 2013); and the onset of the COVID-19 crisis (March 2020).

Global Hedging shock. One contribution of this paper is showing that incorporating emerging market variables enhances the identification of U.S. shocks. This is because U.S. shocks have significant spillover effects on EMEs, so that including those variables can help improve estimators' properties. This is especially evident in the case of the hedging shock. A simple event study shows that during major risk-off episodes, long-term yields in EMEs typically rise (figure 4a). However, impulse responses from the original Cieslak-Pang hedging shock show the opposite effect (figure 4b). In contrast, our model, produces responses that align with observed dynamics: a negative hedging shock leads to higher long-term yields in EMEs (figure 4b)[2]. This is in line with the literature finding that global risk-off shocks tighten financial conditions in EMEs, rather than generating synchronized declines in long-term yields across countries (see, e.g., Albagli et al., 2019; Miranda-Agrippino and Rey, 2020; and Solís, 2025).

[2]Although the impact response is imposed by construction, the IRF from day 1 onwards is unrestricted.



(a) Ten year yield of emerging markets during risk-off episodes

(b) Impulse Response Function of 10-year yield of emerging markets during a risk-off shock

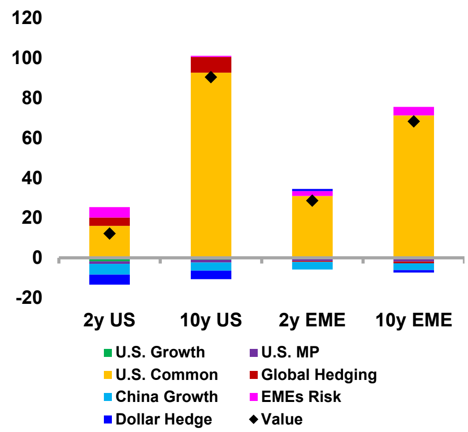
Figure 4. During risk of episodes, 10 year yield of emerging markets tend to rise

Notes: Panel a: T=0 day selection: Apr 26–27, 2010: Greek bonds downgraded to junk status; contagion fears spread; September 13, 2011: On this day, global financial markets were shaken by escalating fears of a Greek default and broader contagion risks across the Eurozone; Mar 9, 2020: "Black Monday I" – Dow falls 2,014 points (-7.8%). Panel b: Cumulated, daily in basis points. Estimates are based on Jordà (2005) local projection approach. The figure displays the impact response to a one-standard-deviation shock. Compares the Cieslak and Pang (2021) shocks (green line) and the shocks that we propose in this paper ("blue line). Dot lines represent a 80% confidence interval.

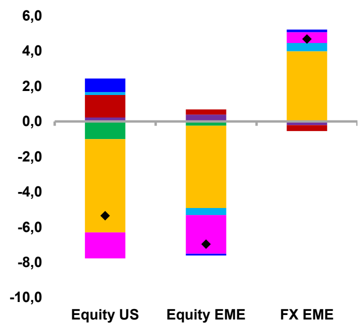
5.2. Decompositions in prominent past events

The purpose of this subsection is to illustrate how the model captures the fundamental forces driving asset price dynamics during episodes linked to major macroeconomic events. We present the cumulative responses of U.S. 2-year and 10-year Treasury yields, the S&P index, as well as the 2-year yield, 10-year yield, and nominal exchange rate of emerging economies across key episodes of global financial stress and policy shifts. Specifically, we examine the Taper Tantrum, the Eurozone debt crisis of 2011, and market reactions to the 2024 Jackson Hole meeting. Importantly, this exercise serves as an *indirect validation* of our approach: rather than imposing narrative restrictions, we assess whether widely accepted narratives are consistent with our empirical estimates.

Taper Tantrum: The Taper Tantrum began in late May 2013, when the Federal Reserve signaled a potential reduction in asset purchases. This triggered a sharp repricing of global term premia, capital outflows from emerging markets, and pressure on local currencies and risky assets. Consistently with that narrative, our SVAR model shows that, between May 22 and September 1, the selloff was driven by a U.S. common risk-premium shock. Long-term yields rose by about 100 basis points in the U.S. and nearly 80 in EMEs, while U.S. equities declined and EM currencies depreciated—consistent with a broad increase in risk premia. The model also identifies a rise in EME risk during this period, that has the largest effect on EMEs equity markets.



(a) Cumulative change in yields (bp)



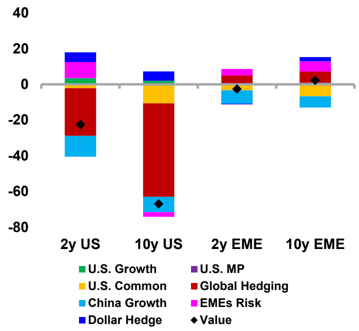
(b) Cumulative change in EME FX and S&P (pp)

Figure 5. Taper Tantrum: cumulative changes and model-based historical decomposition

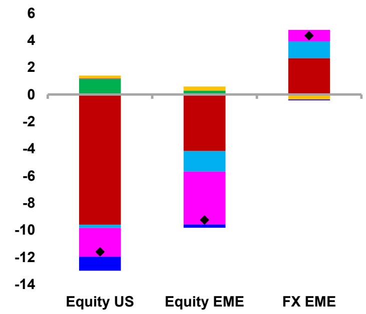
Note: Bars report period changes over 21 May - 1 September 2013. Panel (a) shows yields in bp for US 2y, US 10y, EME 2y and EME 10y. Panel b) shows Equity US, Equity EME and EME FX in pp. positive values denote depreciation against the US dollar. Historical decomposition are based on our SVAR identification.

Euro debt crisis 2010: The Greek crisis began in 2009 with the revelation of large hidden deficits, but it reached its peak in 2010, when market stress across the euro area surged. By mid 2010, solvency fears in peripheral countries drove bond yields sharply higher and triggered a pronounced risk-off episode, with investors fleeing to U.S. Treasuries.

In our SVAR, asset price dynamics on that period are mainly driven by the global hedging shock (typical risk-off), and the EME risk (figure 6). The hedging shock explains most of the over 30 basis point decline in the U.S. 10-year yield, and a relevant proportion of the near to 12% decline of the S&P. In emerging markets, currencies and stock markets declined sharply, but even more than what the global risk-off can explain, reflecting the specific EME component captured by the EME risk shock, consistent with a shock originated in EMEs.



(a) Cumulative change in yields (bp)

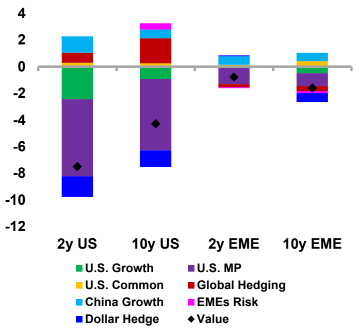


(b) Cumulative change in EME FX and S&P

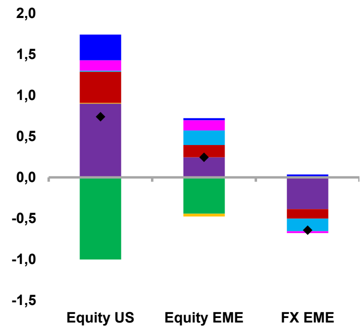
Figure 6. Euro debt crisis 2010: cumulative changes and model-based historical decomposition
Note: Bars report period changes over April 16 - May 10 2010. Panel (a) shows yields in bp for US 2y, US 10y, EME 2y and EME 10y. Panel b) shows Equity US, Equity EME and EME FX in pp. positive values denote depreciation against the US dollar. Historical decomposition are based on our SVAR identification.

Jackson Hole meeting 2024: The Jackson Hole Economic Policy Symposium took place from August 22 to 24, 2024, under the theme "Reassessing the Effectiveness and Transmission of Monetary Policy". During the event, Chair Powell signaled a shift in the Federal Reserve's stance, noting that inflation had moderated and that risks to employment were rising, thereby opening the door to rate cuts. This was not expected by the market and represented a significant U.S. monetary policy shock, as shown in figure 7, which generated a a pronounced decline in short term interest rates. At the same time, this more dovish perception of U.S. monetary policy exerted appreciation pressures on emerging market exchange rates. Results also reveal a negative U.S growth shock, likely reflecting market economic outlook updates after Powell comments on the risks to the labor market. This shock pushed the S&P downwards, partially compensating the positive effects of the more dovish Fed.

While this subsection focuses on event-specific decompositions, the full-sample historical decompositions are provided in figure C.1 of the appendix.



(a) Bonds yield for US and EMEs, basis points



(b) Cumulative change in EME FX and S&P

Figure 7. Historical Decomposition during Jackson Hole

Note: Bars report period changes over 22 - 26 August 2024. Panel (a) shows yields in bp for US 2y, US 10y, EME 2y and EME 10y. Panel b) shows Equity US, Equity EME and EME FX in pp. positive values denote depreciation against the US dollar. Historical decomposition are based on our SVAR identification.

6. Detailed model's results

6.1. Estimated shocks

One of the main criticisms of sign restrictions as an identification strategy is that they generate model multiplicity, by identifying an admissible set of models, rather than point estimates. Each admissible model corresponding to a different admitted draw of Q_i. Consequently, summary statistics such as mean or median impulse responses–commonly used to estimate structural shocks $\epsilon_t(Q_i)$–aggregate information across distinct solutions. Furthermore, while structural shocks are orthogonal within a single draw, there is no guarantee of orthogonality across draws. To address this issue, we implement the approach proposed by Fry and Pagan (2005) and select the median target (MT) solution. This solution corresponds to the draw whose contemporaneous asset price responses to structural shocks are closest to the median response across all admissible models.

Formally, for each $Q_i \in \mathbb{R}$, let $\theta_i = vec(\tilde{A}0(Qi))$ denote the vector of contemporaneous responses. We standardize each solution θ_i by subtracting the element-wise median and dividing by the standard deviation, both computed over the set of models satisfying the identification restrictions:

$$\theta^{MT} = \arg\min_i \left[\frac{\theta_i - median(\theta_i)}{std(\theta_i)}\right]' \left[\frac{\theta_i - median(\theta_i)}{std(\theta_i)}\right]. \tag{5}$$

Figure 8 reports the daily cumulative shocks implied by the MT solution across specifications along with the median solution.

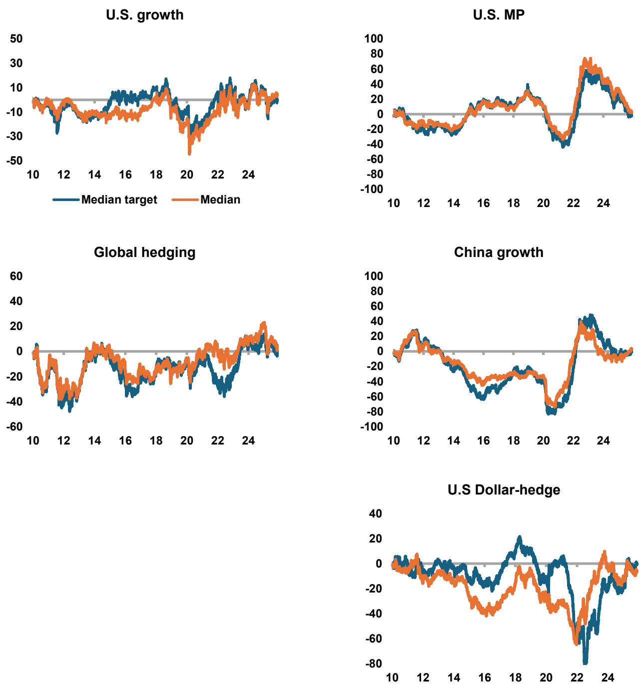


Figure 8. Identified shocks: median and median target
Note: Shocks standardized and cumulated since January 14th 2010.

The comparison between the median shocks and the median target shocks provides insight into the robustness of the identification strategy. When the two coincide closely, it suggests that the distribution of admissible impulse responses is highly concentrated and that the median trajectory is feasible under the structural restrictions. Conversely, noticeable differences indicate that the median-by-period responses are not close to any admissible rotation, reflecting higher uncertainty in the identification. Figure 8 illustrates the cumulated shocks for both approaches, which appear remarkably similar over the full sample, with discrepancies emerging only in specific periods. These deviations are visually amplified by the accumulation process, where small differences in specific periods compound over time. Nevertheless, the correlations showed in table 2 based on original, rather than cumulated shocks, confirm that the two methods produce highly consistent dynamics, reinforcing the conclusion that the identification is robust despite minor cumulative divergences.

U.S. growth	U.S. MP	U.S. Common Risk	Global Hedging	China Growth	EME risk	U.S. Dollar-Hedge
0.92	0.91	0.91	0.90	0.80	0.85	0.74

Note: The table reports the correlation between the *median* and *median target* shocks, both expressed in first differences.

Table 2. Median and median target shocks correlation

6.2. Impulse Response Functions (IRFs)

In this subsection we include all the median target IRFs implicit in our baseline model. The responses are cumulated over a 250-day horizon, and shocks are normalized to have a unit standard deviation on impact. Figure 9 displays the IRFs of all shocks across all variables, computed from Local Projections of each variable to the median target shocks. Reported confidence intervals reflect estimation uncertainty of the median target parameters. In the next section, when comparing our baseline estimation across alternative model specifications, we report the full admissible set of IRFs.

Results shows signs and magnitudes that are consistent with established empirical findings. The U.S. growth shock produces a simultaneous increase in short- and long-term Treasury yields and a significant rise in equity prices, while we impose this on impact, the pattern for $h > 0$ is a result. This positive comovement between yields and equity prices accords with the canonical decomposition of Campbell (1991), in which cash-flow news and discount-rate revisions exert opposing effects on asset prices. During expansionary episodes, the former dominates: higher expected real activity raises expected future earnings sufficiently to outweigh the concurrent upward revision in discount rates, generating the procyclical comovement between equity prices and interest rates observed in the impulse responses. Andersen et al. (2007) provide high-frequency evidence that positive real activity surprises induce simultaneous increases in equity prices and bond yields. A growing body of evidence documents the conditions under which yields and equity prices comove positively or negatively, with cash-flow news and discount-rate revisions as the operative mechanisms (see e.g., Cieslak and Schrimpf, 2019; Cieslak and Pang, 2021). Furthermore, the rise in EME yields are consistent with the evidence showing that U.S. growth shocks generate tightening effects abroad through higher expected global rates and reduced risk appetite in EMEs (see, e.g., Fratzscher, 2014; Hoek et al., 2022; Lodge and Manu, 2022). Together, these magnitudes confirm that our identification strategy correctly captures the cross-market transmission of U.S. macroeconomic news.

The strong and immediate rise in short-term U.S. yields and the simultaneous decline in equity prices following a U.S. monetary policy shock accord with the transmission mechanism embedded in the standard New Keynesian framework: a contractionary policy surprise raises the discount rate applied to future cash flows without a corresponding revision in expected earnings, compressing equity valuations while simultaneously pushing yields upward. This negative stock-bond comovement is precisely the pattern exploited in the high-frequency identification literature to distinguish genuine policy surprises from information shocks — where the central bank reveals its private assessment of economic conditions and both yields and equity move in the same direction. Jarociński and Karadi (2020) formalize this distinction, using the sign of the stock-bond comovement as the identifying restriction, while Cieslak and Schrimpf (2019) provide the systematic decomposition of yield and equity movements around monetary policy announcements into cash-flow and discount-rate components. The relatively larger response of short-term relative to long-term yields, both on impact and at longer horizons, is consistent with the predictions of the expectations hypothesis for transitory monetary policy shocks. If markets anticipate that the policy rate will revert to its neutral level, the long-term yield, as a weighted average of expected future short rates, responds by less than the short-term yield on impact and converges faster thereafter.

Importantly, this pattern emerges endogenously from the model rather than being imposed by the identification scheme, which restricts only the on-impact responses of the variables. International spillovers also show the expected patterns, raising both short- and long-term yields in emerging markets and depreciating their currencies. Albagli et al. (2019) and Ahmed et al. (2021) provide direct evidence of this yield transmission channel, documenting the pass-through of U.S. monetary policy shocks to EME term structures. The concurrent currency depreciation reflects the amplification of these spillovers through risk-taking and capital flow channels: Bruno and Shin (2015) establish the role of global banks in transmitting U.S. monetary conditions through risk appetite, while Rey (2015) and Avdjiev et al. (2019) document the broader synchronization of EME financial conditions with the global financial cycle. The magnitude and speed of these spillovers, particularly the strong response of EME exchange rates, accord with the view of Miranda-Agrippino and Rey (2020) that U.S. monetary policy operates as the central driver of global financial conditions, with EME asset prices and capital flows adjusting rapidly to Federal Reserve decisions.

The U.S. common-risk shock generates a rise in long-term yields and a fall in equity prices in both the U.S. and EMEs, consistent with a global repricing of risk in which investors reduce their exposure to risky assets and demand higher compensation across the maturity spectrum. The simultaneous increase in yields at both short and long horizons reflects a generalized reduction in the demand for bonds — a liquidity-preference mechanism whereby heightened risk aversion raises the term premium along the entire yield curve, as documented by Cochrane and Piazzesi (2005)). The concurrent decline in equity prices accords with the discount-rate risk mechanism emphasized by Cieslak and Pang (2021), whereby increases in the compensation for bearing risk compress asset valuations simultaneously across markets. Thus, our results are consistent with the interpretation that after these shocks markets require higher compensation for long-duration risk, which drives up term premia while simultaneously depressing equity valuations. The magnitude of the long-term yield response in EMEs is also consistent with the literature showing that term premia in emerging markets react strongly to global risk shocks (Albagli et al., 2019; Solís, 2025).

Similarly, the global hedging (risk-off) shock produces a decline in U.S. yields and a rise in equity prices—followed by higher EME long-term yields. This is consistent with the classic "flight-to-safety" dynamic, in which global risk-off episodes trigger portfolio reallocation toward safe U.S. assets, compressing Treasury yields and boosting equity valuations in advanced economies, while simultaneously raising sovereign risk premia and financing costs in emerging markets (Fratzscher, 2009; Bruno and Shin, 2015; Avdjiev et al., 2019). As highlighted in section 5.1, our IRFs improve upon the original Cieslak-Pang hedging shock: while their model predicts a decline in EME long-term yields during risk-off episodes, our specification matches observed behavior, where long-term EME yields typically rise in stress episodes. As a result, the model captures the empirically relevant feature that global risk-off shocks tighten financial conditions in EMEs, rather than generating synchronized declines in long-term yields across countries.

The China-growth shock raises EME yields, and appreciates their currencies and equities, in line with the global spillovers documented in Gutierrez et al. (2024). The magnitudes of these responses, particularly the appreciation of emerging-market currencies, reflect the strong sensitivity of EME assets to China-related news. Positive shocks to Chinese real activity transmit globally through trade, commodity-price, and risk-sentiment channels, boosting asset prices and strengthening currencies in economies with close trade and financial linkages to China. As documented by Fernández et al. (2021), the risk-sentiment channel is particularly relevant here, global financial cycles driven by shifts in risk premia generate synchronized movements in EME asset prices, with positive growth news from China operating as a favorable shift in global risk appetite that reduces required risk compensation across emerging markets.

The EME-risk shock produces a sharp rise in EME long-term yields, a fall in EME equity prices, and a depreciation of EM currencies—effects that match the asset-price dynamics observed during well-known stress episodes such as the September 2011 European-debt crisis, the June 2013 Taper Tantrum, and the onset of COVID-19 in March 2020. As documented in the event-study section, these episodes coincide with spikes in the identified EME-risk shock and are marked by capital outflows, higher sovereign spreads, and abrupt currency depreciation. These dynamics are consistent with a large literature showing that country-specific risk shocks in emerging markets trigger sudden increases in sovereign and currency risk premia, leading to sharp repricing of long-duration assets (Uribe and Yue, 2006; Longstaff et al., 2011; Augustin, 2018). This pattern is also in line with evidence that EM-specific shocks have large effects on local yields and equities (e.g., Lodge and Manu, 2022; Albagli et al., 2019), and that their magnitude tends to exceed that of global shocks during periods of acute regional vulnerability. In such episodes, deteriorating domestic fundamentals and heightened rollover risk tend to amplify local term premia and weaken currencies (Broner et al., 2013; Fratzscher, 2014). Our IRFs also reflect the empirical fact—emphasized in the paper—that EME-risk shocks disproportionately affect long-term yields relative to short-term rates, a feature widely documented in studies of EM crises, where uncertainty about fiscal sustainability, default risk, and exchange-rate regimes is priced at longer maturities (Du and Schreger, 2016; Augustin et al., 2019).

Finally, the dollar-hedging shock stands out for jointly increasing U.S. yields, lowering the dollar, and U.S. equity prices–precisely the anomalous pattern observed in 2025 that cannot be accounted for by the two-factor risk structure in Cieslak and Pang (2021). The literature on the international monetary system provides the conceptual foundation for this mechanism: Gourinchas et al. (2019) characterize episodes in which a loss of confidence in U.S. assets generates simultaneous outflows across asset classes, decoupling the dollar from its traditional safe-haven role. Lilley et al. (2022) provide complementary evidence that fluctuations in cross-currency hedging costs can produce precisely this configuration — higher U.S. yields coinciding with dollar depreciation — by altering the relative attractiveness of dollar-denominated assets to foreign investors.

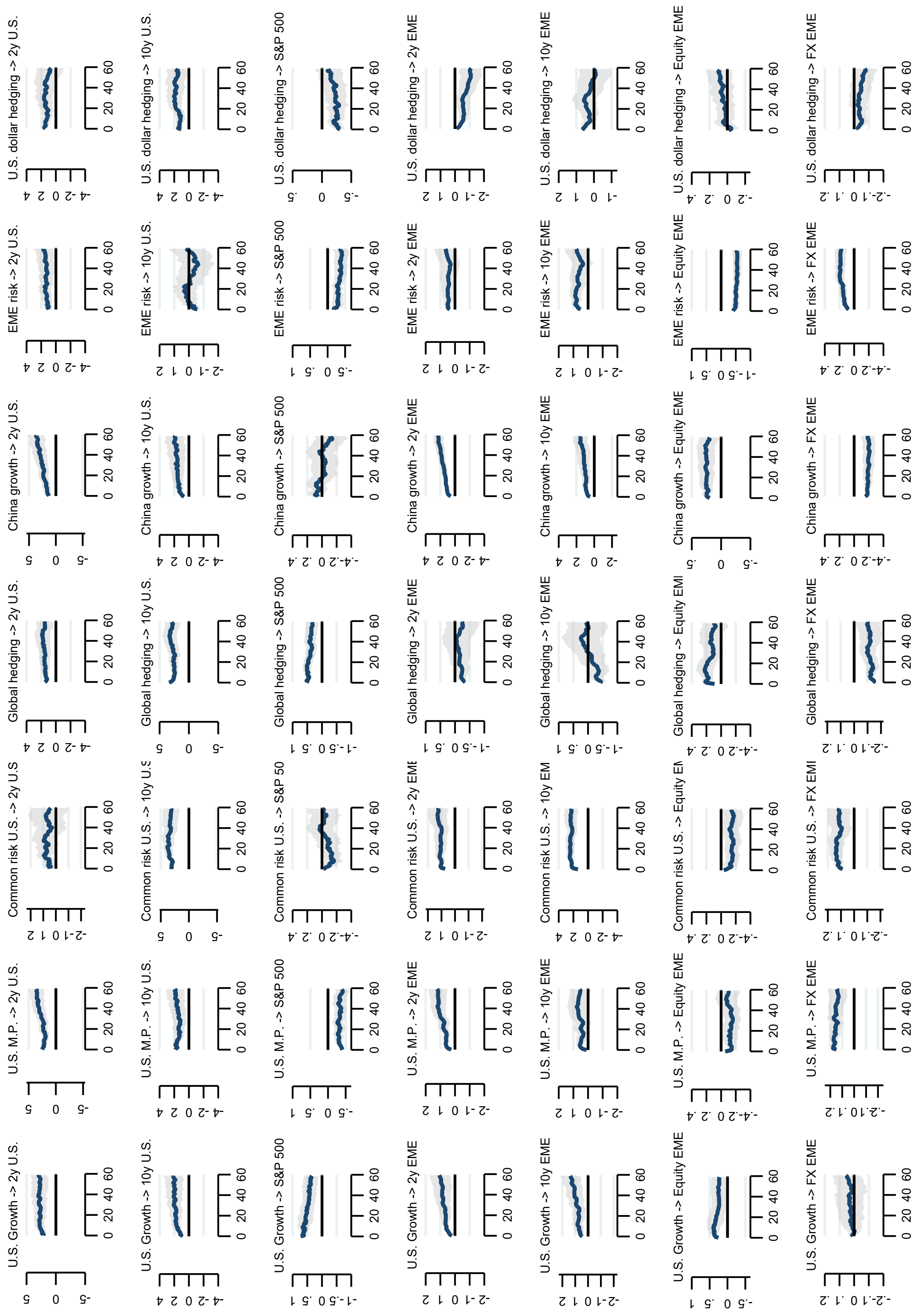


Figure 9. Impulses Response Functions of the Global Model

Notes: Cumulated. X-axis correspond to days. Yields in basis points, FX and stocks in percentage points. The gray shaded area denotes the 95% confidence interval, computed from Local Projections.

6.3. Forecast Error Variance Decomposition (FEVD)

We now turn to the variance decomposition of asset price fluctuations, for the median target estimation. The forecast error variance decomposition (FEVD) quantifies how much of the variability in each asset is explained by each structural shock.

Estimations reveal substantial heterogeneity in the drivers of financial variables (figure 10). As expected, U.S. monetary policy explains a large share of the variation in U.S. 2-year Treasury yields and generates notable international spillovers. Importantly, U.S. monetary policy explains around 30% of the variance of emerging-market exchange rates, indicating a strong external transmission channel through currencies' valuations. These findings matches the broad consensus reported in studies such as Albagli et al. (2019), Ahmed et al. (2021), and Rey (2015) which document strong cross-border propagation of U.S. policy shocks via term-premium and risk-taking channels.

The global hedging shock (typical risk-on/off shifts), also explains a significant proportion of the variance of U.S. assets, and has relevant global spillovers. EMEs exchange rate standout with more than 20% of its variance explained by this shock. This is also consistent with the literature emphasizing the global financial cycle and flight-to-safety dynamics, including Miranda-Agrippino and Rey (2020) and Lodge and Manu (2022).

The importance of U.S. common-risk shocks for long-term yields in both the U.S. and EMEs mirrors the patterns in Cieslak and Pang (2021), and aligns with evidence that global discount-rate shocks primarily operate through term premia, particularly at longer maturities (Albagli et al., 2019; Solís, 2025).

U.S. growth shocks have a substantial impact on the S&P 500, accounting for nearly 50% of its variance. However, their global spillovers are more limited. The most notable transmission occurs in emerging market equity index, where they explain more than 20% of the variance, consistent with evidence that real activity news propagates internationally through expected global growth and valuation channels (Fratzscher, 2014; Lodge and Manu, 2022).

China-growth shocks appear most relevant for EMEs exchange rates and 2-year yields, explaining almost 30% of their variance, likely reflecting its effects on commodity prices. This is consistent with recent findings on the global reach of Chinese macroeconomic news (Gutierrez et al., 2024; Ahlquist, 2013; Fernández et al., 2021). The impact of the China growth shock on U.S. assets appears more limited.

The emerging-market risk shock has a sizable impact on EM equities, accounting for more than 50% of their variance. This reflects documented episodes like the 2010 European debt crisis and the 2013 Taper Tantrum, where country-specific vulnerabilities generated or amplified global shocks. The prominence of this shock is consistent with the literature showing that EM-specific risk shocks dominate asset-price fluctuations during periods of acute stress (Uribe and Yue, 2006; Longstaff et al. (2011); Augustin, 2018).

Finally, the dollar-hedging shock accounts for a small share of all asset price' variation, reflecting its relevance only at the very end of our sample.

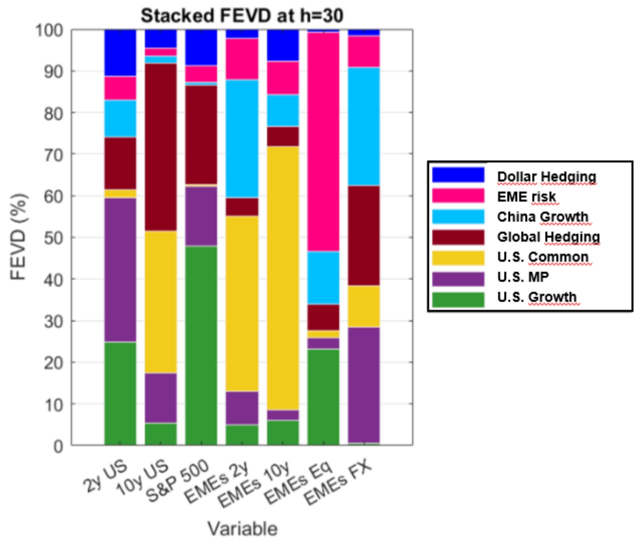


Figure 10. Forecast Error Variance Decomposition

7. Robustness checks

We assess the robustness of our results using both an expanded global model and simpler reduced model. The baseline model is parsimonious and delivers theory-consistent IRFs, historical decompositions, and FEVDs. The reduced model checks whether the findings hold with an even smaller information set, while the global model tests their validity in a richer setting using additional variables and an alternative estimation approach based on recently developed Bayesian methods.

The reduced specification is designed to assess whether our main conclusions persist in a leaner environment. It includes six observables (rather than seven of the baseline model): the 2-year and 10-year U.S. Treasury yields and the S&P index for the United States, together with the 10-year bond yield and the nominal exchange rate for emerging economies, and the Hang Seng stock index. The inclusion of the Hang-Seng is motivated in having a more direct approach for identifying the China-growth shock. With these variables, the model identifies six structural shocks, the same set as in the baseline specification, except for the EME risk shock, which is excluded from the analysis. Excluding this shock avoids the difficulty of distinguishing China-growth shocks from EME-risk shocks, which share all the identification scheme, except for their effects on EMEs exchange rate. We estimate this reduced model using the same frequentist approach applied to the baseline. The identification matrix for the reduced specification is reported in Table 3.

The extended specification differs from the baseline along two dimensions. First, we broaden the set of observables by incorporating eight additional variables grouped as follows: (i) U.S. variables: the 5-year yield, which sharpens the identification of U.S. term-structure shocks following Cieslak and Pang (2021), and the U.S. Dollar Index to capture dollar strength relative to developed economies; (ii) a block of developed economies–processed in a similar fashion to the emerging-

Table 3. Reduced Model Identification Matrix

		(1)US Growth	(2)Global Hedging	(3)US Common	(4)US MP	(5)Dollar Hedge	(6)China Growth
US	2-year	1	-1	1	1	1	NaN
	10-year	1	-1	1	1	1	NaN
	Equity	1	-1	-1	-1	-1	1
EME	10-year	NaN	NaN	1	1	NaN	1
	H-S	NaN	-1	-1	-1	NaN	1
	FX	NaN	1	1	1	-1	-1

Notes: Sign and magnitude restrictions imposed for structural identification. NaN remain as unrestricted values. The model considers magnitude restrictions between variables for the following shocks. For US Growth: 2y US > 10y US and 10y US > 10y EME. For US Hedging Risk: 10y US > 2y US and 10y US > 10y EME. For US Common Risk: 10y US > 2y US; US MP: 2y US > 10y US. For China Growth: 10y EME > 10y US. Finally, we impose intra-variable magnitude restrictions on different shocks. For 2y US: US growth + US MP > US Common Risk + US Hedging Risk; for 10y US, the opposite. These latter intra-variables restrictions are adopted from Cieslak and Pang (2021).

economies block described earlier– for which we include the 2-year and 10-year yields, and an equity-market variable; and (iii) two commodity prices: oil and copper, together with the Hang Seng index to account for the specific dynamics of China's equity market. Second, given the increased dimensionality and complexity, we estimate this extended specification using Bayesian methods, relying on the algorithm proposed by Korobilis (2022). The final model comprises 15 variables and identifies seven structural shocks, with the identification matrix presented in Table 4.

Table 4. Extended Model Identification Matrix

		(1)US Growth	(2)Global Hedging	(3)US Common	(4)US MP	(5)Dollar Hedge	(6)China Growth	(7)EME Risk
US	2-year	1	1	1	1	1	NaN	NaN
	5-year	1	1	1	1	1	NaN	NaN
	10-year	1	1	1	1	1	1	-1
	Eq.	1	1	-1	-1	-1	1	-1
	DXY	1	-1	1	1	-1	-1	1
DEV	2-year	1	NaN	1	1	NaN	NaN	NaN
	10-year	1	NaN	1	1	NaN	1	NaN
	Eq.	1	1	-1	NaN	-1	1	-1
EME	2-year	NaN	-1	1	1	NaN	1	1
	10-year	NaN	-1	1	1	NaN	1	1
	Eq.	NaN	1	-1	-1	-1	1	-1
	FX	NaN	-1	1	1	-1	-1	1
OTHERS	Oil	NaN	NaN	NaN	NaN	NaN	1	NaN
	Copper	NaN	NaN	NaN	NaN	NaN	1	NaN
	Hang-Seng	NaN	NaN	NaN	NaN	NaN	1	NaN

Notes: Sign and zero restrictions imposed for structural identification. NaN remain as unrestricted values. The model considers magnitude restrictions between variables for the following shocks. For US Growth: 2y US > 10y US, 5y US > 10y US and Eq US > Eq EME. For US MP: 2y US > 5y US, 5y US > 10y US. For US hedging risk: 5y US > 2y US, 10y US > 5y US and 10y EME > 2y EME. For US common risk: 5y US > 2y US, 10y US > 5y US. For EME Risk: 2y EME > max2y DEV, 2y US, 10y EME > 2y EME, and Eq. EME > maxEq DEV, Eq US. For China growth: HS > maxEq EME, Eq DEV, Eq US, Copper > Oil, Eq EME > Eq US, and 2y EME > 10y EME. For Dollar HEdge Eq US > Eq EME. Finally, we impose intra-variable magnitude restrictions on different shocks. For 2y US: US growth + US MP > Global Risk + US Risk-Avg; for 10y US, the opposite.

In a nutshell, we estimate a reduced-form VAR of n global asset prices, $y_t = \Phi x_t + \varepsilon_t$, where ε_t has covariance matrix Ω. To recover structural shocks, Korobilis (2022) assumes a factor structure for the reduced-form innovations $\varepsilon_t = \Lambda f_t + \nu_t$, such that $\Omega = \Lambda\Lambda' + \Sigma$. In the reduced form error decomposition, f_t is an $r\times 1$ vector of common components (structural shocks), Λ is the $n\times r$ loading matrix, and Σ is diagonal. Substituting into the VAR yields $y_t = \Phi x_t + \Lambda f_t + \nu_t$, which can be written as a structural form $A_1 y_t = B_1 x_t + f_t + A_1 \nu_t$, with $A_1 = (\Lambda'\Lambda)^{-1}\Lambda'$. Under the large-$n$ result of Bai (2003), $A_1\nu_t \to 0$, implying $f_t \equiv u_t$ are the structural shocks. This factor decomposition allows us to impose sign, zero, and magnitude restrictions directly on Λ to identify r structural shocks with $r(r-1)/2$ restrictions. Crucially, since shocks are sampled only within the admissible region of the parameter space, this Bayesian approach avoids the accept–reject inefficiency typical of frequentist sign-restricted SVARs, yielding substantially faster and more stable estimation.

7.1. Comparison of Results

Key qualitative patterns are preserved across specifications (signs, relative magnitudes across maturities, and persistence). In line with this, Table 5 reports correlations between the baseline median-target shocks and their counterparts in the robustness models. Most shocks display high daily-frequency correlations—exceeding 0.6 in both the reduced and extended versions—suggesting that the identification of the main structural drivers is not sensitive to model size.

The main exception is the dollar-hedging shock, whose correlations fall below 0.1 in both robustness checks. This pattern is consistent with the fact that this shock is relevant only toward the end of the sample and is more tightly linked to variables that are omitted in the reduced model and diluted within the larger set of observables in the extended model.

Beyond pointwise correlations of median-target shocks, an additional and complementary way to assess cross-model consistency is to compare the full distributions generated by the admissible sets themselves. Figure 11 shows substantial overlap between the 20$^{\text{th}}$ and 80$^{\text{th}}$ percentiles of the admissible-set shock distributions across specifications, implying that shocks identified under the baseline are broadly compatible with the set of admissible realizations under the alternative models (and vice versa). Taken together, the evidence from Table 5 and Figure 11 supports the stability of the structural interpretation across model configurations and, therefore, the reliability of the baseline results.

	US growth	US MP	US Common	US Hedging	China Growth	EME Risk	Dollar-Hedge
Reduced	0.81	0.59	0.86	0.72	0.62	0.66	0.08
Extended	0.28	0.93	0.80	0.68	0.70	0.67	0.1

Note: The table reports the correlation across reduced and extended *median target* shocks and baseline *median target* shocks .

Table 5. Shocks correlation: reduced and extended model respect to baseline model

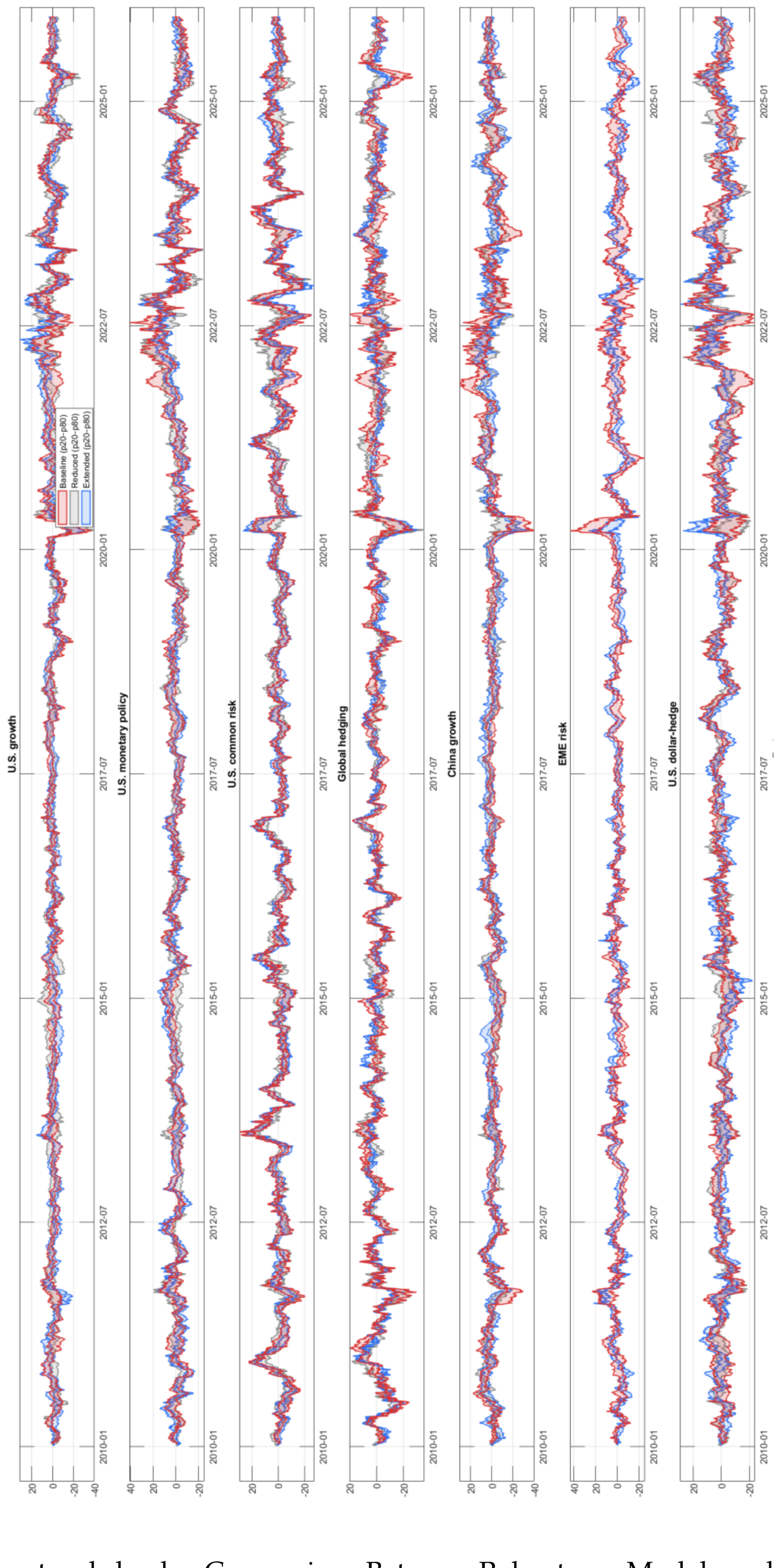


Figure 11. Structural shocks: Comparison Between Robustness Models and the Baseline

Notes: Series are smoothed using a one-quarter moving average and reported in standard deviation units. Shaded bands represent the 20th–80th percentile range across all admissible sets generated under each model.

8. Financial Conditions Index

In this section, we develop a Financial Conditions Index (FCI) derived from the structural shocks identified in the paper.

A wide range of FCIs has been developed in the literature. For instance, the Chicago Fed's National Financial Conditions Index (NFCI) uses principal component analysis on 105 financial indicators–including money markets, credit spreads, and equity valuations–to extract a common factor summarizing overall financial conditions.

Other approaches, such as the Goldman Sachs FCI, assign weights to selected financial variables based on their estimated impact on GDP, derived from stylized macroeconomic models. This index includes the federal funds rate, 10-year Treasury yield, trade-weighted dollar, credit spreads, and equity valuations.

Similarly, the Federal Reserve's FCI-G, introduced in 2023, aggregates seven financial variables using weights from structural models like FRB/US. It explicitly incorporates the dynamic transmission of financial conditions to household spending and business investment, capturing both the magnitude and timing of their effects on economic activity.

While these indexes provide valuable insights, they typically abstract from the nature of the shocks driving financial variables. For example, an increase in the 10-year Treasury yield may reflect either a growth shock or a risk shock—each with opposite implications for the activity. Our approach complements existing FCIs by isolating these structural drivers, offering a more nuanced view of how financial conditions affect the real economy.

For a given country, our proposed FCI, aggregates structural shocks using a dynamic weighting scheme. The weights are derived from the estimated dynamic multipliers (impulse responses) of each shock on macroeconomic aggregates such as GDP, consumption or investment. We compute those multipliers as the local projections' coefficients of the estimated shocks on macroeconomic aggregates:

$$\Delta y_{t+h} = c^h + \phi_1^h s_{1,t} + \Theta_1^h(L) s_{1,t} + \phi_2^h s_{2,t} + \Theta_2^h(L) s_{2,t} + \ldots + \phi_6^h s_{6,t} + \Theta_6^h(L) s_{6,t} + \epsilon_{t+h}, \tag{6}$$

where, Δy_t is the demean log difference of the seasonally adjusted macroeconomic aggregate, $s_{i,t}$ is the i^{th} shock identified in this paper, $\Theta_i^h(L)$ is a polynomial lag with no independent term, ϕ_i^h are the dynamic multipliers we use to compute the FCIs. We also include a set of dummy variables for the COVID period (Q1 to Q3.2020). To match the frequency of the macroeconomic aggregate to that of the shocks, we just aggregate the shock to the required lower frequency.

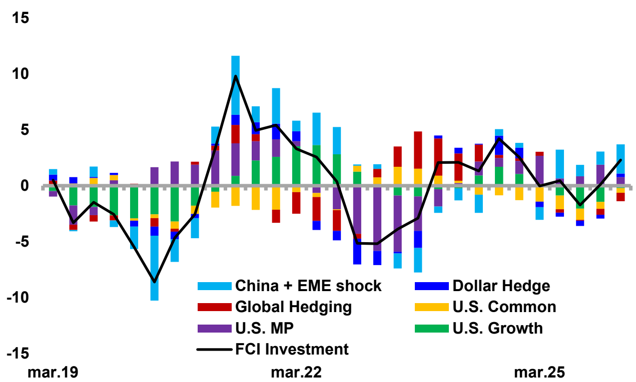
Then, we define the FCI for the macroeconomic aggregate Y as:

$$FCI_t^Y = \sum_{h=1}^{P} \sum_{i=1}^{6} \phi_i^h s_{i,t-h} \tag{7}$$

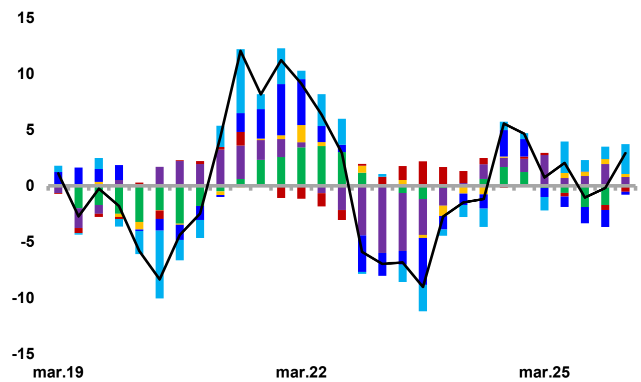
Relative to conventional FCIs that establish linear relations between asset prices and indicators of economic activity, our framework can be thought as a non-linear alternative. Within our setting, an identical change in, say, interest rates may generate heterogeneous effects on the FCI, depending on the underlying shock generating that change. It could even be the case that these effects differ in sign. Another relevant advantage of this strategy is that it allows interpretation and scenario analysis, which is essential for policy makers.

The results of our FCI, for U.S. investment and consumption for the period 2019.Q1-2025.Q3, are shown in figures 12a and 12b, respectively. During the COVID period (2020), financial conditions for both consumption and investment tightened substantially, with the most pronounced downward pressures stemming from risk-related factors (common risk and risk-off dynamics), combined with weaker growth prospects. At the same time, monetary policy acted as a force toward looser financial conditions in the context of the zero lower bound. However, the more restrictive monetary policy in 2022–when the Federal Reserve began raising interest rates–acted as a tightening force for both components, particularly for consumption.

Since early 2025, various forces have emerged, influencing different components of financial conditions in distinct ways. Initially, weaker growth prospects and heightened uncertainty–driven by tariff announcements and institutional tensions–led to a tightening of financial conditions. Over time, however, trade agreements, optimism surrounding artificial intelligence, the perception that tariffs would have limited economic impact, and expectations of more accommodative monetary policy helped offset these initial pressures.



(a) Financial condition index for U.S investment



(b) Financial condition index for U.S consumption

Figure 12. Financial Condition Index for United States, period 2011.Q4-2025.Q3.
Note: annual growth, percentage points.

Figure 13 compares our FCI with other available alternatives for the full sample Q1.2011-Q3.2025.

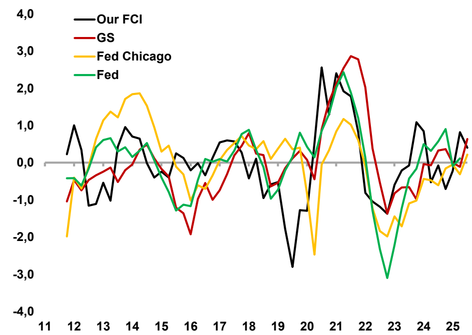


Figure 13. Financial Condition Index comparison, sample Q1.2011-Q3.2025
Notes: Normalized indexes. A rise in the index indicates better financial conditions.

8.1. Comparison with other FCIs

One approach to assess the performance of our FCI relative to existing alternatives is to compare their out-of-sample predictive accuracy of economic aggregates. Specifically, at the end of each quarter, we use each FCI to nowcast U.S.internal private demand, using the following equation:

$$\Delta y_t = c + \Phi(L)\Delta y_{t-1} + +\Theta(L)\Delta FCI_{i,t} + \epsilon, \tag{8}$$

where Δy_t is the demean log difference of U.S internal demand at quarter t, $\Phi(L)$ and $\Theta(L)$ are lag polynomials, and $FCI_{i,t}$ is the i^{th} FCI at quarter t. We run this regression on an expanding window basis so as to generate 26 nowcasts, corresponding to quarters Q1.2017 to Q2.2025.

For each indicator, we compute the root mean squared error (RMSE) of the nowcast series. As a benchmark, we also estimate a simple autoregressive model of order two, AR(2). The RMSEs of the FCIs are then compared to that of the AR(2) model, and the results are presented in table 6 as ratios relative to the AR(2) RMSE. All financial conditions indicators outperform the AR(2) benchmark in terms of predictive accuracy. Notably, our proposed indicator delivers the largest improvement, achieving the lowest RMSE ratio relative to the AR(2). This suggests that our FCI may capture relevant information for nowcasting economic activity that is not embedded in other FCIs. According to Dieblod-Mariano tests, differences accross FCIs are not statistically significant, what may reflect small samples issues. In next section however, we find statistically significant differences for emerging economies.

To further evaluate the performance of our Financial Conditions Index (FCI), we analyze the quarters in which it delivers the largest relative improvements in RMSE. A particularly informative episode is Q2.2024, when GDP—measured as a weighted average of fixed investment and private consumption—expanded by 0.1 percent quarter-on-quarter. In contrast, all alternative FCIs

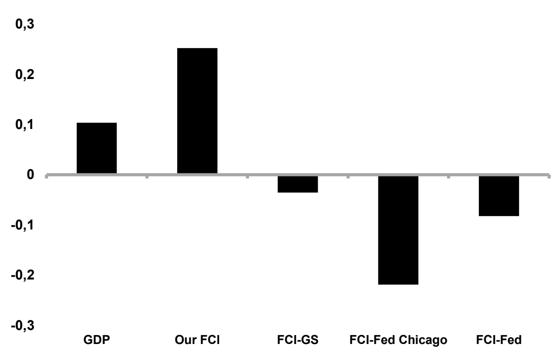
Table 6. RMSE Ratios of Financial Conditions Indicators to Nowcast U.S. internal private demand (ratios relative to AR(2) RMSE)

FCI-GS	FCI-Fed Chicago	FCI-Fed	Our FCI
0.92	0.85	0.94	0.76

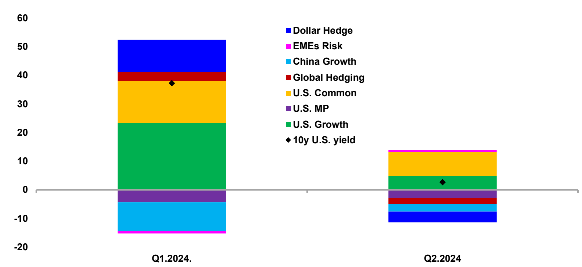
Notes: For our FCI, we construct a weighted average of the Investment FCI and the Consumption FCI, where the weights correspond to their respective shares in GDP.

projected a contraction ranging between 0.1 and 0.2 percent quarter-on-quarter, whereas our FCI correctly anticipated an expansion 14a .

During that quarter, the U.S. 10-year Treasury yield increased by approximately 3 basis points. Crucially, one-third of this rise was driven by a growth shock, which accounted for roughly 5 basis points and is associated with expansionary economic conditions. Furthermore, developments in the previous quarter (Q1.2024) are also relevant for understanding this outcome: over that period, the 10-year yield rose by nearly 40 basis points, with more than 20 basis points attributable to growth shocks and an additional 3 basis points to risk-on shocks—both of which signal positive macroeconomic dynamics. (figure14b).



(a) Q2.2024 GDP growth (qoq, weighted average of fixed investment and consumption): actual vs. FCI estimates (%)



(b) Decomposition of 10-year Treasury yield in Q1.2024 and Q2.2024 (basis points)

Figure 14. Q2.2024 GDP growth, FCIs nowcast for thatg period and decomposition of 10-year Treasury yield

Because the proposed methodology explicitly identifies the underlying structural shocks driving financial variables, it allows for a more accurate interpretation of interest rate movements. In particular, it can distinguish between yield increases associated with favorable economic conditions and those driven by contractionary forces. Consequently, even in episodes such as Q2.2024—when interest rates rose modestly—our FCI correctly projects GDP expansion, in contrast to alternative FCIs that implicitly treat higher rates as uniformly restrictive and therefore incorrectly signal a contraction. Moreover, the forward-looking nature of the index allows shocks realized in previous quarters to continue influencing current financial conditions, further enhancing both forecast and nowcast performance.

9. FCIs for emerging economies

To extend the analysis beyond the U.S., we construct country-specific financial conditions indices (FCIs) for selected Emerging economies using a structural VAR with exogenous components (SVAR-X). The exogenous block consists of the seven structural shocks identified in the baseline global model, while the endogenous block includes local shocks related to monetary policy, growth, common risk, and hedging risk. For each economy, the endogenous variables comprise the 2-year and 10-year local bond yields, the nominal exchange rate against the U.S. dollar, and equity returns from a representative stock market index. This structure allows us to isolate the contribution of global shocks to local financial conditions while accounting for domestic dynamics. Table 7 shows the identification matrix.

Table 7. SVAR-X Identification Matrix

		(1)Local Growth	(2)Local MP	(3)Local Common	(4)Local Hedging
Local	2-year	1	1	1	1
	10-year	1	1	1	1
	Equity	1	-1	-1	1
	FX	-1	-1	1	-1

Notes: Sign and magnitude restrictions imposed for structural identification. NaN remain as unrestricted values. The model considers magnitude restrictions between variables for the following shocks. For local Growth: 2y > 10y. For Local MP: 2y > 10y. For Local Common Risk: 10y > 2y. For local Hedginf: 10y > 2y. Finally, we impose intra-variable magnitude restrictions on different shocks. For 2y: local growth + local MP > local Common Risk + local Hedging Risk; for 10y, the opposite.

The resulting FCIs inherit a structural interpretation: they aggregate the impact of shocks on local financial variables, enabling us to distinguish whether tightening or easing conditions originate from global factors or domestic sources. We then benchmark these indices against widely used alternatives and evaluate their predictive performance for domestic demand (consumption and investment), showing that our SVAR-X-based measure delivers superior forecast accuracy. A full empirical application of this approach is deferred to future work; here we focus on illustrating its robustness and comparative performance.

Similarly to Table 6, Table 8 compares the RMSE of each of these country-specific FCIs with

Goldman Sachs' FCI for the corresponding country. As in the U.S. case, our RMSEs are lower—indicating stronger predictive power for economic activity—and, in this instance, the differences are statistically significant.

Table 8. RMSE ratio versus an AR(2) benchmark for nowcasting LATAM investment

Country	FCI–GS	Our FCI
Brazil	0.88	0.52*
Chile	0.91	0.77*
Mexico	0.73	0.52*

Notes: Asterisks denote statistical significance relative to the Goldman Sachs (Diebold-Mariano test). *90%; **95%; ***99%.

10. Conclusion

This paper presents a structural framework to identify and interpret the fundamental drivers of global asset prices and financial conditions in a systematic way. Our framework enhances traditional financial conditions indices by linking asset price dynamics to their structural sources, enabling more precise and interpretable assessments of the macro-financial landscape.

The paper's key contributions are both methodological and policy-oriented. Methodologically, it improves U.S. shock's identification by incorporating emerging market data, highlights the importance of China growth shocks for emerging markets asset prices dynamics, and introduces the novel dollar-hedging risk shock. On the policy side, it proposes a real-time monitoring tool and a shock-based Financial Conditions Index that supports scenario analysis and cross-country comparisons.

Empirical results show that the proposed shocks explain major financial episodes more accurately than existing models, particularly in emerging markets. Additionally, by linking economic activity indicators to high frequency structural shocks, the proposed Financial Conditions Index not only allows for structural interpretation, but also produces better nowcasts of economic activity than available alternatives. The framework captures heterogeneous international transmission mechanisms and provides insights that are not attainable through reduced-form approaches. Results are robust to significant changes in the specification of the model and the estimation strategy. Overall, we believe that this paper offers a valuable tool for central banks and policymakers seeking to understand and affect local financial conditions.

Future research may focus on evaluating how well our strategy captures financial developments within individual emerging economies. Assessing whether it produces coherent narratives around major country-specific events would provide an additional validation of the framework. Another avenue is the development of a high-frequency version of our Financial Conditions Index (FCI), which would enhance its real-time monitoring capabilities.

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11. Appendix

A. Euro-dollar and rate differential relationship

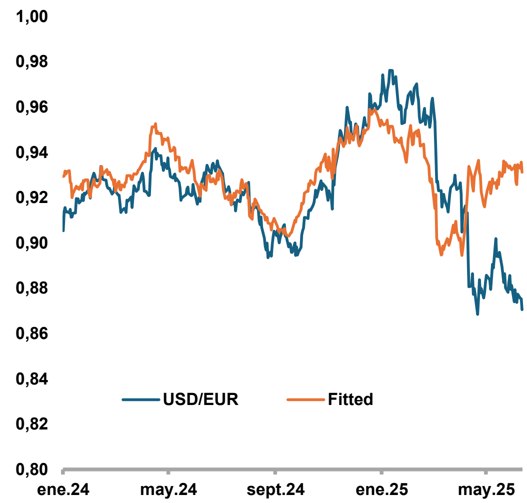
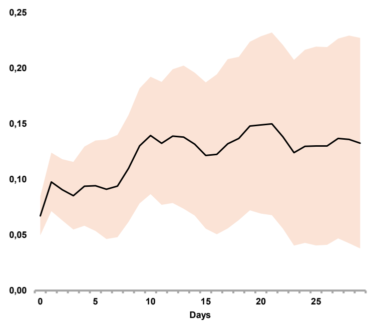
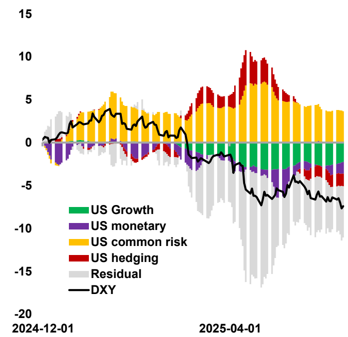


Figure A.1. Euro-dollar and rate differential relationship
Note: OLS regression between the USD/EUR exchange rate and the 10-year interest rate differential between US and German bonds.

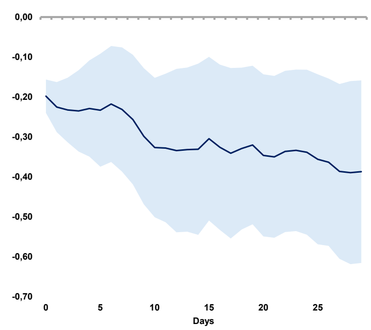
B. IRFs and Historical Decomposition from Cieslak and Pang (2021) shocks





(a) IRFs of DXY to a common premium shock

(b) HD of DXY (Cieslak and Pang, 2021)

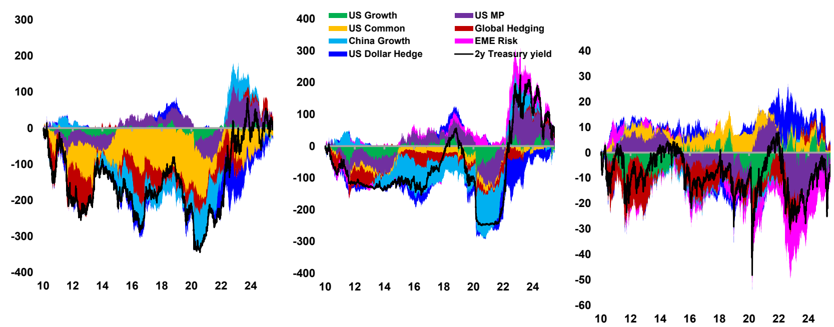


(c) IRFs of EMEs' stock prices to a common premium shock

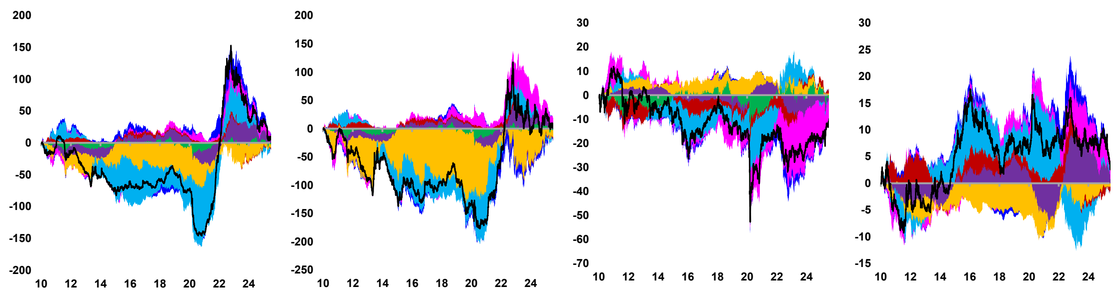
Figure B.1. IRFs and Historical Decomposition from Cieslak and Pang (2021) shocks

Notes: Panel (a) shows impulse responses of the DXY index to a common premium shock. Panel (b) decomposes DXY movements based on IRFs. Panel (c) shows the average cumulative stock price response in EMEs (Chile, Brazil, Colombia, Mexico) to the same shock. IRFs are estimated using Jordà (2005) local projection method and responses correspond to one-standard-deviation shocks. All results are cumulative and expressed in basis points.

C. Historical Decompositions: Full-sample



(a) 10 year U.S Treasury yield **(b)** 2 year U.S Treasury yield **(c)** S&P 500



(d) 2 year EMEs yield **(e)** 10 year EMEs yield **(f)** Equity EMEs **(g)** FX EMEs

Figure C.1. Historical decompositions full-sample.
Note: Cumulated since 2010. Yields in basis points, FX and stocks in percentage points.

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