Drivers of the Global Financial Cycle

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Abstract

Existing literature finds that U.S. monetary policy has powerful effects in driving the Global Financial Cycle (GFC). We examine how important U.S. monetary policy shocks are relative to other shocks in an estimation framework that allows for simultaneous identification of multiple shocks without timing or sign restrictions. We find that the most important driver is a shock to U.S. corporate bond spreads, or the excess bond premium. This shock is orthogonal to shocks to U.S. monetary policy, leverage of financial intermediaries, interest rate spreads, credit supply, risk aversion, and the macroeconomy. U.S. monetary policy shocks are important but considerably less so. We conclude that the hegemon of the U.S. in global financial systems may be rooted in the centrality of its financial intermediaries, and the dollar, rather than the Fed itself.

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1 Introduction

There is well-accepted evidence that significant commonalities exist between the movements of credit aggregates, credit flows, and asset prices across countries—referred to as the global financial cycle (e.g., Rey (2013), Miranda-Agrippino & Rey (2020b), and Miranda-Agrippino & Rey (forthcoming)). Emerging-market economies in particular are subject to large gross capital inflows and outflows as market volatility and risk premiums rise and wane (Kalemli-Ozcan (2019), di Giovanni et al. (2021)). Correlations among risky asset returns internationally are particularly high during crises such as the 1998 Russian debt crisis, the 9/11 terrorist attacks, the global financial crisis, and the Covid-19 pandemic. Studies that address what drives the global financial cycle focus on the key causal role of U.S. monetary policy, a salient view that has received extensive attention from academia (Bekaert et al. (2013), Bruno & Shin (2015), Adrian & Shin (2014), Miranda-Agrippino & Rey (2020a), Miranda-Agrippino & Rey (2020b), Degasperi et al. (2021), and Brauning & Ivashina (2020)); policymakers (Rey (2013), Bernanke (2017)); and media (Thomas (2015)).

Notwithstanding the prominence of these views, and despite literature suggesting that several shocks could conceivably be important drivers of the global financial cycle, there is little analysis of the contribution of U.S. monetary policy shocks relative to other shocks. We fill the gap in this paper, estimating the contributions of several different shocks to explaining movements in variables emphasized in the GFC literature. We use as baseline a medium-to-large scale heteroskedasticity-based structural VAR model as in Brunnermeier et al. (2021) (BPSS). We include the global financial cycle factor estimated in Miranda-Agrippino & Rey (2020b), together with a large number of economic and financial variables, and identify their structural disturbances. Our identification does not require timing or sign restrictions, and most appealingly, it allows for multiple causal channels through which credit conditions, monetary policy, and real activity interact dynamically. Our work thus complements and extends recent cutting-edge work including: Miranda-Agrippino & Rey (2020b) who highlight that their medium-to-large scale Bayesian VAR allows them to control for the responses of many variables to the one shock they identify (U.S. monetary policy shocks); Degasperi et al. (2021) who quantify spillovers of U.S. monetary policy shocks in a large Bayesian global VAR and find that tightening shocks have large contractionary spillovers onto both advanced and emerging economies; and Boehm & Kroner (2023) who use an event study to show that U.S. macroeconomic news releases have large effects on international equity prices and the VIX, while being agnostic about the source of structural disturbances.

Most consequentially, we include in the VAR the Gilchrist & Zakrajšek (2012) (GZ) corporate bond credit spread index and identify shocks to this spread that are orthogonal to shocks to U.S. monetary policy, leverage of financial intermediaries, interest rate spreads, credit supply, and the macroeconomy.[1] GZ show that their credit spread index, mostly driven by its EBP component, has considerable predictive ability for U.S. economic activity. We demonstrate that there is significant explanatory power of these spreads globally.

We derive three main results. First, orthogonalized innovations to U.S. corporate bond spreads ("credit spreads") or excess bond premium (EBP) are the most important driving force of the global financial cycle, especially at short to medium horizons.[2] These shocks have large and immediate effects on the GFC factor of Miranda-Agrippino & Rey (2020b), risk aversion, the U.S. dollar exchange rate, and global equity prices. Positive credit spread shocks significantly lower the GFC factor and leverage of (especially U.S.) financial intermediaries, and significantly lower output in the U.S. and abroad. The same shocks lead to a significant retrenchment of global risk appetite, a slight Fed monetary policy easing, dollar appreciation, and a fall in global stock prices. Strikingly, we find that innovations to U.S. credit spreads account for about 70% of the volatility of the Miranda-Agrippino & Rey (2020b) factor in the short run, about 40%-50% in the medium term, and 20%-30% in the long run. This baseline result is robust to changes in the variables included in the baseline VAR, to alternative time-varying variance regimes in our identification, to different monetary policy indicators, alternative approaches to identification of shocks, and to incorporating a large number of shocks emphasized elsewhere in the literature, such as shocks to the leverage of financial intermediaries, different uncertainty shocks, credit supply shocks, and global risk aversion shocks.

Second, Fed monetary policy shocks do play an important role in explaining the global financial cycle, but their impact is quantitatively smaller than that of U.S. corporate bond spreads. At a maximum, U.S. monetary policy shocks account for about 15% to 30% of the volatility of the global factor across VAR specifications.[3] U.S. monetary policy shocks also have significant effects on the leverage of U.S. banks, U.S. term spreads, global risk aversion, and global equity prices, but these effects are usually smaller than the effects of GZ spread shocks.[4]

[1] GZ employ an extensive micro-level dataset of secondary market prices of corporate bonds and extract from this a residual component known as the excess bond premium—a measure of U.S. credit market sentiment computed from deviations in the pricing of corporate bonds relative to the measured default risk that represents variation in the pricing of default risk.

[2] Although we primarily use the spreads, we find that replacing them with the EBP index yields similar conclusions. BPSS (2021) also use the GZ corporate bond spread series—rather than EBP—in their VAR.

[3] Dropping the GZ corporate bond spread from the VAR does not materially increase the contribution of U.S. monetary policy shocks in explaining the GFC factor; the additional explanatory power goes into the "own shock".

[4] Our findings on the (long) horizon at which U.S. monetary policy shocks become important echo those in the literature, noted below, where some significance is found at 7–10 quarters or later.

Third, identified shocks to banking sector leverage have significant effects on the global financial cycle. A surprise increase in the leverage of financial intermediaries—especially U.S. intermediaries—raises the global factor in the medium term, leads to reductions in global risk aversion, and prompts modest Fed tightening. This supports the emphasis placed on financial intermediary leverage in the theoretical literature (as discussed below).

Related Literature Conceptually, the literature has shown that an important mechanism generating the global financial cycle emerges from the behavior of financial intermediaries. In "quiet" periods of low risk and volatility, intermediaries leverage up and take on more risk. This raises the demand for risky assets during booms but when risk and volatility increase, intermediaries respond by shrinking their balance sheets and deleveraging. If this switch to more risk-averse behavior and lower leverage is sharp enough, risky borrowers who received credit in the boom may not be able to finance themselves and their highly leveraged positions lead to a downward spiral in the financial sector (Adrian & Shin (2014), Bruno & Shin (2015), and Akinci et al. (2022)). Related to this, Morelli et al. (2022) model global financial intermediaries who purchase risky securities internationally and drive borrowing-cost and consumption fluctuations in emerging-market economies. Aggregate shocks transmit through intermediaries' net worth, the magnitude of which depends on the degree of frictions they face in financing risky investments. Davis & van Wincoop (2021) also provide a theory to account for changes in asset prices and capital flows over the global financial cycle. Their model focuses on global risk-aversion shocks. Their key vulnerability is associated with leverage: following a rise in global risk aversion, net borrowers of safe assets deleverage through negative net outflows of risky assets and positive net outflows of safe assets. As noted by Bernanke (2017), strong though those co-movements in risky asset prices across countries may be, there are alternative interpretations as to their ultimate source: the GFC could be driven by common shocks, and even if the GFC reflects the transmission of shocks across countries it is not obvious where these shocks originate.

In pioneering early work, Forbes & Warnock (2012) find a prominent correlation between global risk (measured by VXO) and extreme capital flows, by disaggregating capital flows by foreign and domestic investors. Rey (2013) finds that shocks to the Federal Funds rate explain from about 4% to 17% of the variance of the VIX, depending on the exact specification of the (Cholesky) VARs. In their 4-variable Cholesky VAR, Bruno & Shin (2015) find that shocks to the Fed Funds rate explain almost 30% of the variance of the VIX at horizons longer than 10 quarters. Bekaert et al. (2013) find that monetary policy shocks account for over 20% of the variance of risk aversion at horizons

longer than 7 quarters in a four-variable VAR, and in a six-variable VAR, the monetary policy shock accounts for about 12% of the variance of risk aversion at horizons longer than 10 quarters. In their exhaustive review of the literature, Miranda-Agrippino & Rey (forthcoming) characterize the global financial cycle through eight stylized facts. These include that one global factor accounts for around a quarter of fluctuations in risky asset prices around the globe, that this factor is highly correlated with measures of risk appetite such as the VIX, and that global factors account for a sizable percentage of the variance of gross capital flows. In addition, these authors highlight the important role of the Federal Reserve in driving the global factor in asset prices, capital flows, and measures of risk aversion, financial conditions, spreads, and credit.

Our paper contributes to the GFC literature by (i) identifying multiple interpretable shocks that correspond to disturbances to the economy and financial markets, without relying on timing or zero restrictions; (ii) distinguishing these shocks from U.S. monetary policy shocks; and (iii) estimating the relative importance of all shocks to explaining the GFC. Papers with some of these features include the following. Cerutti et al. (2019) focus on the fraction of variation in capital flows explained by global influences. Their OLS regression R2 values lead them to conclude that U.S. fundamentals explain at most 25% of the variation in capital flows. Habib & Venditti (2019) use a combination of zero and sign restrictions to identify four shocks: U.S. monetary policy; U.S. aggregate demand; a global financial shock; and a geopolitical risk shock. They find that changes in global risk caused by pure financial shocks have the largest impact on capital flows, followed by U.S. monetary policy shocks. Boehm & Kroner (2023) follow Faust et al. (2007) by implementing a high-frequency event study of the intraday effects of news surprises such as U.S. nonfarm payroll employment, and argue that U.S. monetary policy is not the main mechanism behind movements in global asset prices. As noted by both Faust et al. (2007) and Boehm & Kroner (2023), surprises about U.S. macroeconomic variables are not structural shocks, making interpreting their effects challenging. In addition, these papers are limited to studying asset prices as outcome variables.

Finally, our work is in the spirit of Brunnermeier et al. (2021), who examine feedback between U.S. credit shocks and U.S. output using a large-scale SVAR model that jointly identifies multiple causal channels. They conclude that, "Shocks to credit spreads generate substantial contractions in output and credit, as do monetary policy shocks. The monetary policy shocks have somewhat larger effects, on average, than the spread shocks. The monetary policy shocks explain a substantial part of the variation in the credit aggregates and in one of the spread variables. These shocks are separately and stably distinguished from one another because of their variability peaking at different

points in history (e.g., the Volcker disinflation versus the Great Recession)." We also rank the contribution of U.S. monetary policy shocks relative to other identified shocks but in a global context. Another important finding of Brunnermeier et al. (2021), which derives from their multiple-shocks identification, is that the long-run negative response of output to credit growth is essentially all attributed to endogenous monetary tightening in response to output and inflation growth. We rule out such endogenous monetary policy responses as a key determinant of the GFC factor.[5]

In the next section, we describe our data and estimation strategy that allows for various feedback channels between monetary policy, real activity, and financial variables and hence is new to the GFC literature. Our variance decomposition exercises allow us to provide a ranking of the relative importance of a large number of shocks, providing greater understanding of the role of Fed monetary policy in driving the global financial cycle. In Section 3, we document new evidence that U.S. corporate bond spreads play the predominant role in driving the global financial cycle, especially at horizons up to two or three years. Our results imply that U.S. credit spreads or EBP—which closely mirror movements in capital and balance sheet conditions of key U.S. financial intermediaries—contain significant information about effective risk-bearing capacity in the financial sector not only in the U.S. but also worldwide. Finally, although our paper focuses on econometrically identifying and decomposing the relative contribution of multiple shocks rather than fully explaining what triggers each shock, we discuss in Section 4 interpretations of our findings in light of the dominance of the U.S. dollar (Bertaut et al. (2021)), U.S. centrality in the global financial network (Miranda-Agrippino et al. (2020)), and global risk panics (Bacchetta & Van Wincoop (2013)). The confluence of our results is consistent with the idea that the hegemon of the U.S. in the global financial system may be rooted in its powerful financial intermediaries rather than the Fed itself.

[5] Alternative approaches that would not rely on (recursive) timing restrictions include external instruments (Stock et al. (2012) and Mertens & Ravn (2013)), sign restrictions (Faust (1998) and Uhlig (2005)), and contemporary sign-restricted narrative approaches such as Ludvigson et al. (forthcoming) and Arias et al. (2018). In Section 2, we discuss the relative merits of different procedures and the arguments in favor of a heteroscedasticity-based approach. See also Brunnermeier et al. (2021) and Wolf (forthcoming), Bertsche & Braun (2022).

2 Econometric framework and Data

2.1 Motivation and shock identification

Let $\boldsymbol{y}_t$ be the vector of n observed variables of interest and the general structural form VAR be:

$$C_0 \boldsymbol{y}_t = \boldsymbol{c} + \sum_{j=1}^{p} C_j \boldsymbol{y}_{t-j} + \boldsymbol{\epsilon}_t, \tag{1}$$

where C_0, a $n \times n$ matrix, characterizing the simultaneous relationship among variables included in the system, $\boldsymbol{c}$ is an $n \times 1$ constant vector, C_j $(j = 1, \ldots, p)$ are $n \times n$ coefficient matrices, and $\boldsymbol{\epsilon}_t$ is the vector of structural shocks.

To identify the structural shocks we use for our baseline an identification by heteroscedasticity method following Brunnermeier et al. (2021). Two appealing features of this method for our purposes are that it (i) allows for a large number of variables and shocks, while (ii) not relying on potentially dubious timing and sign restrictions. There are, of course, alternative approaches to identification in structural VARs, the most common being zero restrictions on C_0, long run response restrictions, sign restrictions on impulse responses, narrative approaches, and external instruments. Much of the literature has focused on identifying only one shock, often a U.S. monetary policy shock. Our goal is to identify multiple shocks that correspond to additional disturbances to the economy and financial markets and are distinct from a U.S. monetary policy shock. As argued by Brunnermeier et al. (2021), identification through heteroskedasticy lets us do this with more plausible assumptions than with alternative approaches. For example, external instruments, as used by Miranda-Agrippino & Rey (2020b) to identify only a U.S. monetary policy shock, would require that we find for *each identified structural shock* an observed variable that is correlated with that shock and not correlated with any other structural shock. This approach is feasible when there are, e.g., one monetary policy shock (Gertler & Karadi (2015), Miranda-Agrippino & Rey (2020b)) and the instrument is the high-frequency change in Federal Funds futures prices around FOMC policy announcements, or two fiscal policy shocks (Mertens & Ravn 2013). But for our purposes this approach would be unwieldy: there are many variables that are likely correlated with financial market disturbances, but none that plausibly uncorrelated with any other source of economic disturbances.

Our heteroskedasticity-based Bayesian SVAR (HB-SVAR) framework requires that the variances of structural shocks vary across time regimes. In particular, the set of regimes splits the sample range $\mathcal{T} := \{1, \ldots, T\}$ into historical periods featuring distinct variability in major economic variables. We

denote the regime set as $\mathcal{M} \coloneqq \{1, ..., M\}$, with variance matrix $\Gamma_{m(t)} = E\left[\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t'\right]$ for each $m(.) \in \mathcal{M}$. The function $m : \mathcal{T} \mapsto \mathcal{M}$ maps dates into corresponding regimes. We apply the same normalization to average cross-period variances to be 1 as in Brunnermeier et al. (2021), namely

$$\frac{1}{M} \sum_{m=1}^{M} \gamma_{i,m(t)} = 1, \quad \forall i \in \{1, \ldots, n\} \tag{2}$$

where $\gamma_{i,m(t)}$ is the ith diagonal entry of $\Gamma_m(t)$.[6] Given this restriction together with the reasonable assumption that each pair of variables differs in variance in at least one period (as justified in the next section), we can uniquely identify all n^2 parameters of C_0 up to permuting the order of rows, or flipping the sign of an entire row.[7]

In our baseline analysis, we split the data series into six regimes summarized in Table 1. The first regime corresponds to the Volcker disinflation period during which Taylor-type rules describing the Fed's setting of the policy rate exhibited high variance. The second regime captures the recovery period from the early 1980s recession, and also includes some distinct dynamics due to the S&L crisis. The third regime is the "Great Moderation", characterized by less erratic monetary policy and more predictable macro aggregates. The fourth regime is the financial crisis, during which many macro variables, and especially financial variables, became significantly more volatile. The fifth regime is the zero lower bound period, with negligible variance in monetary policy. The final period is characterized by the most recent monetary policy normalization by the Fed. Our regimes are very similar to those in Brunnermeier et al. (2021), whose sample period goes through 2015. Our more recent data set thus incorporates the (pre-pandemic) post-liftoff monetary policy normalization period. Notice that the regimes chosen by BPSS mainly capture events in the U.S. economy, consistent with the objective of their paper. Since we focus on the global economy, it is reasonable to examine robustness to alternative regimes based more on global considerations. We do this in Appendix section B, examining "global regimes" that include the 1997 Asian financial crisis and the European debt crisis. There we show that results are highly robust, and note that our identification remains consistent as

[6] Using this normalization, we actually restrict the impulse response functions to be the same shape across different regimes but they are allowed to have different sizes.

[7] The basic idea to prove this result is that the reduced form residual variance-covariance matrix for regime m can be written as $\Sigma_m = C_0^{-1}\Gamma_m(C_0^{-1})'$, so for any two regimes s and t we have

$$\Sigma_s^{-1}\Sigma_t = C_0'\Gamma_s^{-1}\Gamma_t(C_0^{-1}). \tag{3}$$

This takes the form of an eigenvalue decomposition and rows of C_0 (which are the eigenvectors) are uniquely determined up to scale as long as the diagonal elements of $\Gamma_s^{-1}\Gamma_t$ are unique (i.e., no k, l satisfying $\gamma_{s,k}/\gamma_{t,k} = \gamma_{s,l}/\gamma_{t,l}$). A formal proof of this can be found in Lanne et al. (2010).

Note that the major potential failure of this identification strategy does not rest on insufficient cross-regime heteroskedasticity, since it is essentially without doubt that the volatility of economic variables varies over time. The real concern, however, falls on the mis-specification of constant $C(L)$. Brunnermeier et al. (2021) provide evidence that this specification outperforms some models that allow $C(L)$ to vary.

long as there is enough variation in Γ_j across regimes.

Table 1: Baseline Regime Choices (BPSS updated)

	Start	End	Description
1	Jan 1980	Dec 1982	Volcker disinflation
2	Jan 1983	Dec 1989	Recovery from early 1980s recession
3	Jan 1990	Dec 2007	Great Moderation and Greenspan Federal Reserve
4	Jan 2008	Dec 2010	Great Recession
5	Jan 2011	Dec 2015	Zero Lower Bound, Recovery from Great Recession
6	Jan 2016	Apr 2019	Monetary policy normalization

Finally, we follow Brunnermeier et al. (2021) to allow for possible rare events to provide more robust estimates. We model the distribution of $\boldsymbol{\epsilon}_t$ as a mixture of normal distributions,

$$\epsilon_{it} \sim N\left(0, \gamma_{i,m(t)}\zeta_{it}\right) \tag{4}$$

where the random parameter ζ_{it} is assumed to follow an inverse-gamma distribution,

$$\zeta_{it} \sim IG(\alpha/2, 2/\alpha) \tag{5}$$

The specifications in (4) and (5) imply that each ϵ_{it} follows an independent Student-t distribution with unit scale and α degrees of freedom, which is calibrated to be 5.3 by maximum-likelihood estimation out of the sample residuals.

Our basic econometric model has n^2 parameters in C_0, $(M-1)n$ parameters in $\Gamma_m(t)$, and n^2p parameters in C_j together with nT parameters in the t-distributed disturbances. The estimation is conducted by Bayesian method updating inferences conditional on observed data $\{y_1, \ldots, y_T\}$ and initial conditions $\{y_{-p-1}, \ldots, y_0\}$. Our supplementary materials provide more details.

2.2 Data and Variable Construction

We summarize the variables included in our various VAR systems in Table 2. To characterize the GFC, we use the global asset price factor extracted from a dynamic factor model by Miranda-Agrippino & Rey (2020b). The most recently updated version of this series ranges from January 1980 to April 2019, as in Miranda-Agrippino et al. (2020). This version takes into account compositional changes in global markets, largely due to greater visibility of Eastern markets like China after 2010.

As in Miranda-Agrippino & Rey (2020b), we further decompose this global factor series into a (i) global realized variance component, measured by sum of daily returns of the MSCI Index, and (ii) a global risk aversion component, the inverse of the residual of a projection of the global factor onto the realized variance. Our risk aversion series is highly correlated with the VIX index, echoing Figures 2 and 3 in Miranda-Agrippino & Rey (2020b).[8]

We also include the effective Federal Funds interest rate as a proxy for U.S. monetary policy. The Fed Funds rate is effectively stuck at zero during 2008-2015 so we confirm robustness of our results to using the Wu-Xia index (Wu & Xia (2016)). Furthermore, we examine robustness to using U.S. monetary policy shock series identified through external instruments.

Variables characterizing U.S. domestic economic and financial conditions are also modeled. These are the industrial production (IP), personal consumption expenditures price index (PCE), commodity price index (PCM), term spread (TS), and in robustness checks, TED spread (TED) and U.S. effective exchange rate (EER). All of these variables are from the Federal Reserve Bank of St. Louis database (https://fred.stlouisfed.org/) except the effective exchange rate, which is the narrow index retrieved from the BIS (https://bis.org/), and the commodity price index obtained from Bloomberg. Our main financial variable, the U.S. corporate bond spread and excess bond premium (EBP) measure are from Gilchrist & Zakrajšek (2012), Gilchrist et al. (2021).[9]

Next, following Gourinchas & Obstfeld (2012), we construct national domestic credit as the difference between domestic claims to all sectors and net claims to the central government, reported by financial institutions excluding the central bank.[10] This is for the U.S. and fourteen European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain and United Kingdom. This national domestic credit measure basically extends the same series provided by Miranda-Agrippino & Rey (2020b) to April 2019.

For the country-level measure of banking sector leverage we follow Forbes (2012) and calculate it as the ratio between Claims on Private Sector and Transferable plus Other Deposits included in Broad Money of depository corporations excluding central banks. We construct this banking sector

[8] Tian et al. (2022) show that this GFC factor is quite robust to alternative construction strategies.

[9] Our 10-variable baseline VAR model contains six of the ten series used by Brunnermeier et al. (2021). We drop the M1 money supply, TED spread, and the two U.S. credit measures (household and commercial bank) which are the focal series of BPSS. In place of these, as listed in Table 3, we add the GFC factor, LevUS, LevEU, and GIPexUS, consistent with the focus of our paper and the GFC literature. Seven of our ten baseline model variables are included in the baseline global VAR model of Miranda-Agrippino & Rey (2020a). The exceptions are TS, FFR, and PCM.

[10] Specifically, we refer to the Other Depository Corporation Survey available within the IMF's International Financial Statistics (IFS) database and construct Claims to All Sectors as the sum of Claims On Private Sector, Claims on Public Non Financial Corporations, Claims on Other Financial Corporations and Claims on State And Local Government; while Net Claims to Central Government are calculated as the difference between Claims on and Liabilities to Central Government.

leverage measure for the same list of countries as the national domestic credit measure; the EU banking sector leverage is measured as the median value among the fourteen countries. We take the average of the U.S. and the EU leverage to obtain our measure of global bank leverage.

Finally, we include global capital inflows—taken from the BIS—as in Miranda-Agrippino & Rey (2020a), the log of the MSCI global index to capture global stock market dynamics, and the world industrial production index constructed by Baumeister & Hamilton (2019) as a proxy of global real economic activity.

Table 2: Data Series Used

Variables	Description
IP	US industrial production from FRED (code: INDPRO)
GFC	Global factor estimated by Miranda-Agrippino et al. (2020)
RA	Global risk aversion decomposed from GFC
FFR	Federal Funds Effective Rate from FRED (code: DFF)
WX	Wu-Xia Index as in Wu & Xia (2016)
GIPexUS	The world industrial production excluding the US calculated by authors
G inflows	Global inflows all sectors from BIS
PCE	Personal consumption expenditures price index from FRED (code: PCEPI)
PCM	CRB/BLS spot (commodity) price index from Bloomberg
EER	US real effective exchange rate (narrow indices) from BIS
TS	Term spread of US Treasury (GS10 - TB3MS)
GZ	GZ spread as in Gilchrist & Zakrajšek (2012)
TED	TED Spread (MED3 - TB3MS)
DCRTEU	EU Domestic Credit, extended from Miranda-Agrippino & Rey (2020b)
DCRTUS	US Domestic Credit, extended from Miranda-Agrippino & Rey (2020b)
LEVUS	US banking sector leverage, extended from Miranda-Agrippino & Rey (2020b)
LEVEU	EU banking sector leverage, extended from Miranda-Agrippino & Rey (2020b)
MSCI	Global MSCI index downloaded from MSCI website

3 SVAR Results

We describe in Table 3 the variables included in our baseline global VAR (column 1) and our various robustness models (Columns 2-4). We estimate the model with 10 lags at monthly frequency over the sample 1980:1 - 2019:4. We report median IRFs with 68% and 90% posterior uncertainty regions. We estimate different specifications in order to examine robustness to extensions that include exchange rates, domestic credit, risk aversion, and global stock market, an approach similar to that of Miranda-Agrippino & Rey (2020b).

Table 3: VAR Variables

Variable name	Source	Global VARs			
		(1)	(2)	(3)	(4)
		Baseline	Alternative Regimes	Proxy SVAR	Robustness
IP	FRED	✓	✓	✓	✓
PCE	FRED	✓	✓	✓	✓
TS	FRED	✓	✓	✓	✓
PCM	Bloomberg	✓	✓	✓	✓
GZ	GZ	✓	✓	✓	✓
EBP	GZ				✓
FFR	FRED	✓	✓	✓	✓
WX	Wu-Xia				$✓^{@}$
LEVUS	IFS*	✓	✓	✓	✓
LEVEU	IFS*	✓	✓	✓	
GFC	MARb	✓	✓	✓	✓
GIPexUS	OC and BH	✓	✓	✓	✓
EER	BIS				$✓^{*}$
Glob inflows	BIS				$✓^{*}$
DCRTUS	IFS*				$✓^{*}$
GDCRT	OC				$✓^{*}$
MSCI	MSCI				$✓^{*}$
Risk aversion	OC and BEX				$✓^{*}$
Uncertainty	WUI, FU				$✓^{*}$

Notes: variables included in Miranda-Agrippino & Rey (2020b) and our various structural global VARs. Our baseline model specification is identified using the method of Brunnermeier et al. (2021). As noted in the next columns, we also consider alternative regimes to identify our model while using the same set of variables as in the baseline setting. In the various "Robustness" specifications we augment our baseline model by replacing LEVEU with other variables alternatively, as listed in the rows. Here a $✓^{!}$ denotes the robustness check where we replace the GZ spread with EBP; $✓^{@}$ denotes the robustness check where we replace FFR with the Wu & Xia (2016) shadow interest rate; $✓^{*}$ denotes robustness checks where the variable is added to our model in place of LEVEU; MARb refers to Miranda-Agrippino et al. (2020), GZ to Gilchrist & Zakrajšek (2012), Gilchrist et al. (2021), BEX to Bekaert et al. (2021), and BH to Baumeister & Hamilton (2019). WUI is the world uncertainty index of Ahir et al. (2022) and FU is financial uncertainty of Ludvigson et al. (forthcoming). We also check robustness to replacing the GFC factor with the world stock market index (MSCI). OC denotes authors' own calculations and IFS* denotes monthly interpolation of the quarterly original variables.

3.1 Impulse Responses

We report impulse responses from our baseline HB-SVAR in Figures 1 and 2. For improved exposition, and following Miranda-Agrippino & Rey (2020b), we split results in two according to "domestic" and "global" responses. In Figure 1, we show the impulse responses of U.S. industrial production, PCE, the commodity price index, term premium, and the GZ spread following each shock, while in Figure 2 we report the global variable responses.[11] We organize description of the results by shock, highlighting shocks to U.S. monetary policy, Leverage, and GZ spreads.

[11] We also estimated VARs containing only domestic U.S. variables, and display results in the online appendix. These are consistent with findings in Miranda-Agrippino & Rey (2020b).

U.S. monetary policy shocks Column 6 of Figure 1 presents the impulse responses to the U.S. monetary policy shock in the baseline SVAR. A contractionary shock leads to a significant decline in industrial production, commodity price index, and term premium, and a marginally significant increase in the GZ corporate bond spread. In terms of global variable responses (Figure 2, column 6), tighter U.S. monetary policy leads to a large drop in the Miranda-Agrippino & Rey (2020a) global price factor at medium horizons, a drop in global industrial production ex. U.S., and a deleveraging in both U.S. and EU banks. The impulse responses of U.S. bank leverage and EU bank leverage following shocks to domestic U.S. variables are very similar: tighter U.S. monetary policy significantly lowers both, consistent with conventional wisdom.

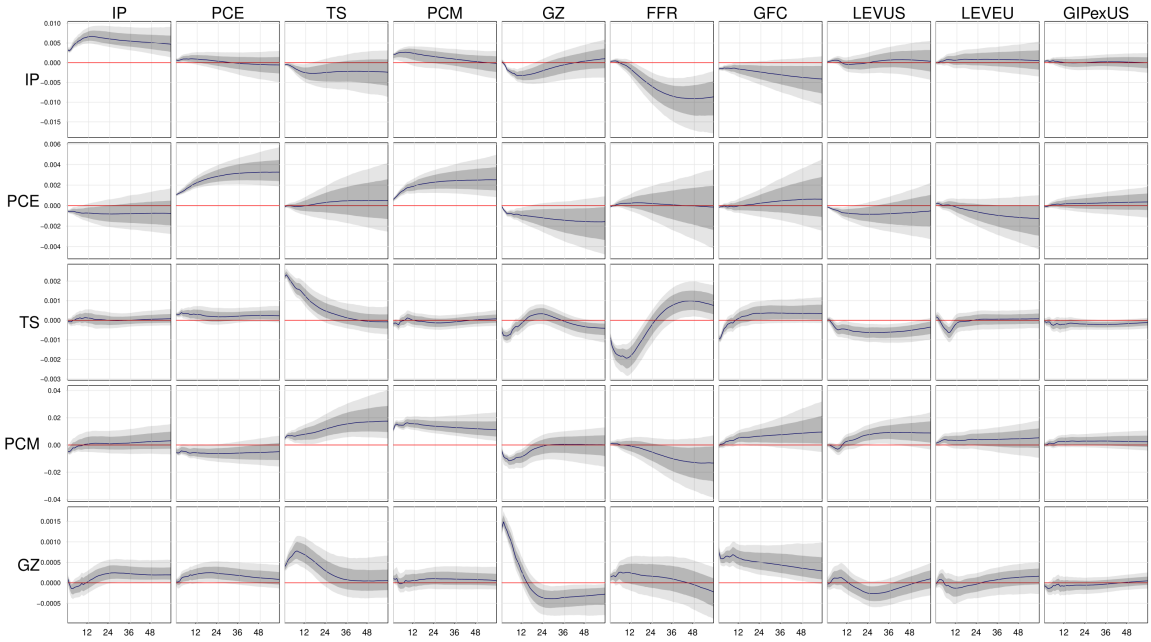


Figure 1: HB-SVAR Impulse Responses: Global VARs, Baseline (1/2)

Note: Impulse responses of U.S. domestic variables with t-distributed errors over 60 months, with 68 percent (dark grey) and 90 percent (light grey) posterior uncertainty regions. Scaled to an "average" period with unit scale.

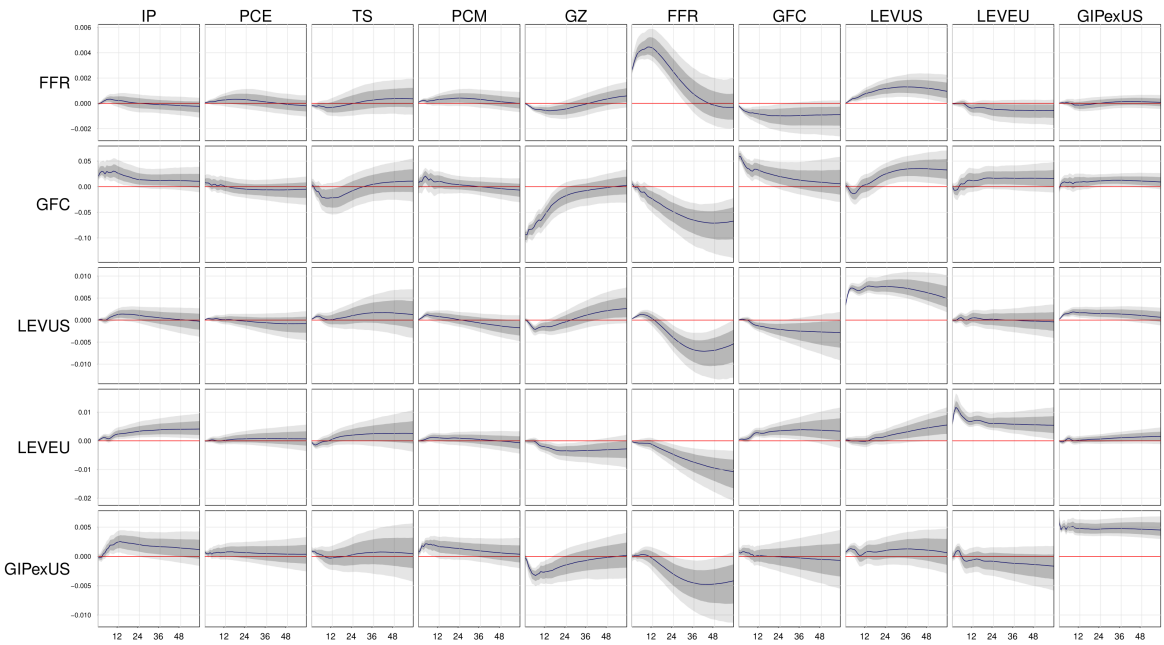


Figure 2: HB-SVAR Impulse Responses: Global VARs, Baseline (2/2)

Note: Impulse responses of FFR, US exchange rate and global variables in model (2) with t-distributed errors over 60 months, with 68 percent (dark grey) and 90 percent (light grey) posterior uncertainty regions. Scaled to an "average" period with unit scale.

Leverage shocks Theoretical accounts of the global financial cycle emphasize the importance of U.S. and global financial intermediaries' leverage positions. As shown in Figure 2, a positive shock to U.S. banking sector leverage has small expansionary effects, as seen in column eight. It leads to an increase in the Miranda-Agrippino & Rey (2020b) global price factor, a small decrease in GZ over the medium term, and a slight tightening of U.S. monetary policy. This is consistent with the theory that leverage is procyclical and the amplification effect adds to systematic risk over time, resulting in a widening of credit spreads. Shocks to U.S. and EU banking sector leverage have opposite-signed effects on U.S. monetary policy, with policy tightening in response to the former, and responding more quickly and by a larger magnitude to leverage shocks in the U.S. banking sector.

GZ credit spread shocks The results above are in line with the risk channel of monetary policy (Bruno & Shin (2015)), and consistent with the impulse responses to Fed monetary policy shocks reported in Miranda-Agrippino & Rey (2020a). In column 5 we display the responses to identified credit spreads shocks (GZ). A shock increase in GZ induces a decline in both U.S. and global industrial production, an immediate drop in PCE and PCM, and flattening in the term structure. In addition, monetary policy loosens, though only slightly. Importantly for our purposes, the GZ shock leads to a sharp decline in the global price factor and a deleveraging of the global banking

sector. These are also consistent with the hypothesis that the deterioration of bank balance sheets and increase in vulnerability in the financial sector can lead to broad pessimism in market beliefs and cause downward pressure on global asset prices and the real economy. Notice that the decline in the GFC factor to the GZ shock cannot be attributed to an endogenous change in U.S. monetary policy both because of the magnitude (small) and the sign (goes the wrong way) of the FFR response.

3.1.1 Structural Shock Volatility

Crucial to our identification of the shocks is the assumption that the variances of each equation in the baseline t-errors model (i.e., γ_{im} in section 2.1) vary across regimes. As discussed by Brunnermeier et al. (2021), a potential pitfall of the estimation strategy would be if there were little variation in the innovation variances, as this would undermine identification and lead to ill-determined results. With this in mind, table 4 reports the estimated regime-varying variances of each equation in the baseline model.

As reported in Table 4, there is strong time-variation in shock variances. The variances of financial shocks, in which we take particular interest, spike during the financial crisis (Period 4). The monetary policy shock, as expected, shows considerably inflated variances during the Volcker disinflation and almost zero variance during the zero lower bound period. In contrast, these variances of the monetary policy and financial market equations are quite stable during the more recent periods including the ZLB and recovery from the Great Recession.

The global asset price factor exhibits the greatest volatility during the S&L crisis and the financial crisis in our sample. Industrial production and commodity prices are most volatile during the Great Recession, but are quite steady during the more recent monetary policy normalization period. The overall consistency between the pattern of global variables and financial shock volatility indicates the important role of financial variables in explaining the global financial cycle.

Table 4: Posterior Median Relative Shock Variances

Shock	Jan 1980-Dec 1982	Jan 1983-Dec 1989	Jan 1990-Dec 2007	Jan 2008-Dec 2010	Jan 2011-Dec 2015	Jan 2016-Apr 2019
IP	1.15	0.50	0.90	2.18	0.64	0.67
PCE	0.62	1.46	1.43	0.85	0.88	0.75
TS	2.58	0.76	0.39	1.81	0.24	0.22
PCM	0.82	1.06	0.80	2.09	0.58	0.67
GZ	0.18	0.34	0.64	3.28	1.03	0.57
FFR	4.76	0.96	0.12	0.13	0.01	0.04
GFC	1.19	1.51	0.71	1.73	0.30	0.52
LEVUS	0.18	0.12	0.35	4.12	0.74	0.50
LEVEU	0.69	0.25	0.29	0.31	2.51	1.93
GIPexUS	0.56	0.99	1.44	0.74	1.11	1.15

Note: The estimates are posterior medians model (1) with t-distributed innovations.

We present further evidence on volatility in Table 5, which lists the four largest posterior median shocks for each variable. The biggest of these, for the monetary policy shock, represents a sudden easing of monetary policy in Feb 1981, during the U.S. recession. Most of the large values for this shock appear during Paul Volcker's non-borrowed reserve targeting regime, which has a large γ for this shock. The largest value in the PCM shocks reflects a great drop in commodity prices in September 2008, largely a result of market turmoil during the sub-prime mortgage crisis. Furthermore, we document a dramatic deleveraging of global banks after the burst of European debt crisis. The IP shock was sharply negative in September 2008, reflecting the large decline in industrial production as the crisis took hold. This is also accompanied by dramatic opening up of corporate credit spreads and break down of global asset prices.[12]

[12] As one can see, the large shocks presented in Table 5 tend to come from regimes with large volatility $\gamma_{i,m(t)}$ instead of shocks dominating the model prediction. As pointed out by BPSS, it would be useful to investigate $\epsilon_{it}/\sqrt{\gamma_{i,m(t)}}$ and focus on the largest "surprises" instead.

Table 5: Largest Residuals For Each Shock

Month	ϵ_{it}	dy_{it}	Month	ϵ_{it}	dy_{it}
IP			FFR		
2008-09-01	-6.101	-0.044	1981-02-01	-12.392	-0.044
2005-09-01	-5.827	-0.025	1981-05-01	9.945	0.037
2008-10-01	5.708	0.026	1980-11-01	8.792	0.032
1982-01-01	-5.137	-0.019	1980-12-01	7.283	0.026
PCE			GFC		
2001-10-01	5.157	0.006	2009-01-01	-8.252	-0.276
2005-09-01	4.489	0.008	1987-10-01	-5.777	-0.871
1985-01-01	4.373	0.004	1986-03-01	4.462	0.084
1990-01-01	3.756	0.006	1982-10-01	3.556	0.135
TS			LEVUS		
1981-05-01	-6.181	-0.028	2001-10-01	5.411	0.023
2008-10-01	5.953	0.007	2009-02-01	-5.281	-0.024
1981-06-01	5.809	0.016	2001-11-01	5.245	0.023
1982-10-01	-4.500	-0.013	2009-01-01	-5.063	-0.022
PCM			LEVEU		
2008-09-01	-7.557	-0.089	2013-04-01	-9.028	-0.071
2008-08-01	-4.032	-0.055	2013-05-01	6.925	0.054
1984-01-01	4.019	0.049	2017-01-01	4.135	0.031
1983-01-01	3.839	0.038	2014-06-01	3.617	0.029
GZ			GIPexUS		
2008-10-01	14.226	0.026	1993-01-01	12.974	0.097
2008-09-01	5.435	0.011	1994-04-01	4.250	0.033
1998-08-01	5.154	0.007	1993-02-01	4.077	0.027
2002-07-01	4.970	0.010	2016-01-01	3.640	0.026

Notes: The estimates are posterior medians from model (2) with t-distributed innovations. The first column is the size of the shock and the second is the contemporaneous impact on the "diagonal" variable.

3.2 Forecast Error Variance Decomposition

Having presented evidence in favor of our identifying assumptions, we return to our assessment of the relative roles played by U.S. monetary policy shocks and (orthogonal) financial market shocks in explaining the global financial cycle. In Figure 3-4 we display the share of forecast error variances explained by each shock.

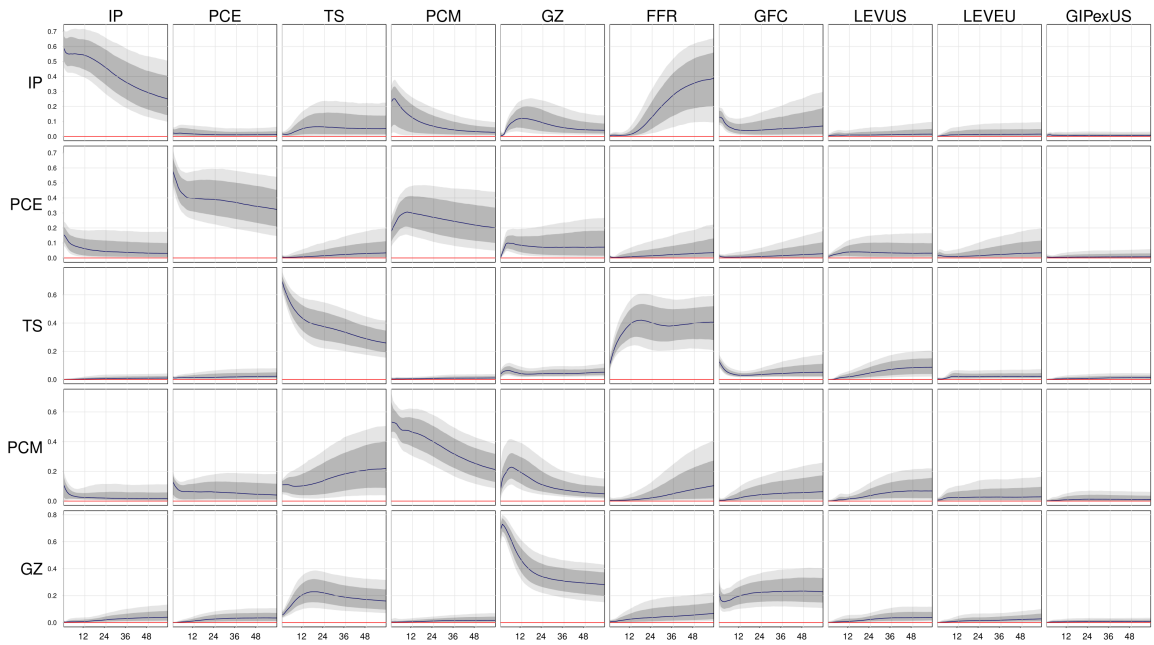


Figure 3: HB-SVAR Variance Decomposition: Global VARs, baseline (1/2)

Note: Forecast error variance decompositions for U.S. variables in the baseline model with t-distributed errors over 60 months, with 68 percent (dark grey) and 90 percent (light grey) posterior uncertainty regions. Scaled to an "average" period with unit scale.

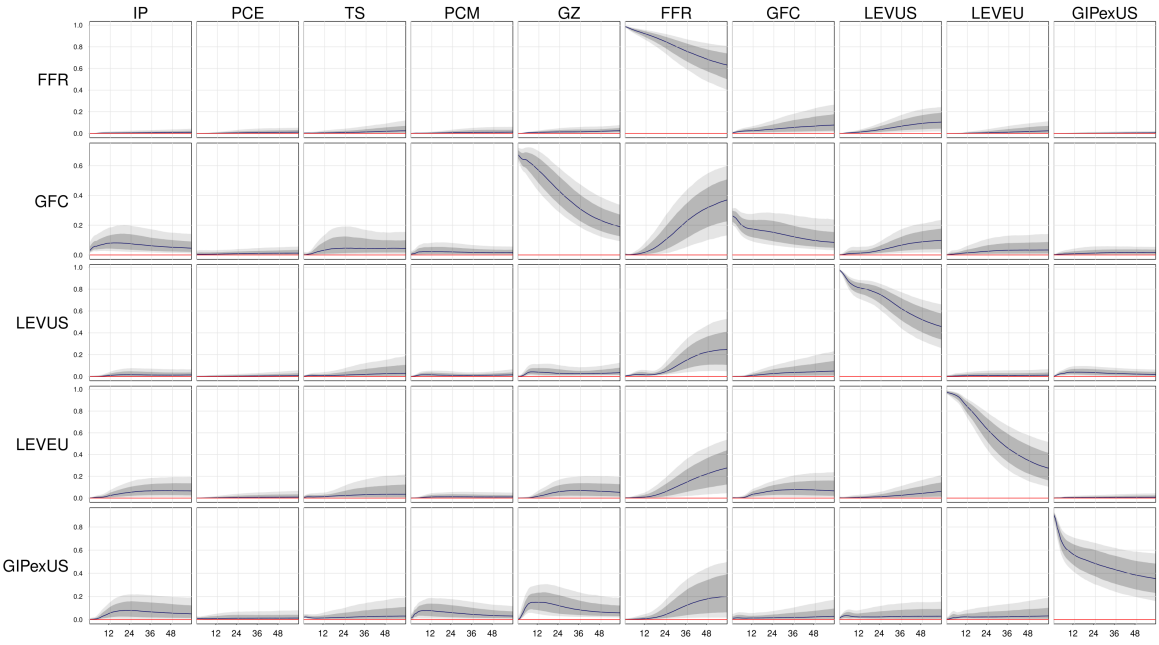


Figure 4: HB-SVAR Variance Decomposition: Global VARs, baseline (2/2)

Note: Forecast error variance decompositions for FFR, U.S. effective exchange rate and global variables in the baseline model with t-distributed errors over 60 months, with 68 percent (dark grey) and 90 percent (light grey) posterior uncertainty regions. Scaled to an "average" period with unit scale.

Figure 3 shows the variance decompositions of U.S. variables. These are largely similar to the results reported by BPSS, e.g., with the U.S. monetary policy shock explaining significant fractions of the forecast error variance of the term spread. This shock also explains significant fractions of leverage at medium to long horizons. Turning to the global VDCs, we see in Figure 4 the striking importance of the GZ shock in explaining the forecast error variance of the global financial cycle factor (column 5). The GZ shock explains over 50% of the variance of GFC on impact and plays a considerable role at short to medium horizons. Although the U.S. monetary policy shock is also significant for the global financial cycle factor, its impact is delayed and much smaller than that of GZ at short horizons (column 6). We also find that the contribution of U.S. banking sector leverage to the VDC of the global factor is significant in the long run, although smaller than that of U.S. monetary policy or the GZ spread.

Our identification strategy allows us to uncover an important role of GZ spreads in driving the global financial cycle. Such dynamics could be driven by the dominant international role of the U.S. dollar and the widespread use of dollar funding by non-U.S. entities, including banks, non-bank financial institutions, and corporate firms. When non-U.S. entities borrow in U.S. dollars, changes in the GZ spreads resulting from, for instance, changes in the outlook for U.S. economic growth and risk aversion, can have important effects on non-U.S. entities' exposures, especially if they are unhedged. In such scenarios, financial globalization paired with the preeminence of the U.S. dollar can lead to synchronized behavior of major participants in the global financial system. That is, high similarity across portfolios lead to high similarity in responses to shocks to U.S. credit conditions, amplifying the reactions across jurisdictions. We explore these ideas further below.

3.3 Robustness to Alternative Regime Choices

As noted above, heteroscedasticity in the disturbances of our VAR equations is a crucial identifying assumption. It is thus useful to know how those time-varying variances differ over alternative regime choices and whether or not those differences alter our conclusions. It turns out that they do not. Recalling that our baseline estimation essentially followed the Brunnermeier et al. (2021) choice of regimes, based on characteristics of U.S. monetary policy, our alternatives are based on an historical partition of global events shown in Table A2. The impulse responses and variance decomposition results based on the alternative regimes are presented in Figure A3 to Figure A6. The results are qualitatively similar to our baseline, with the relative roles of U.S. monetary policy shocks and financial shocks thus unaffected by the choice of time-varying variances regimes.

3.4 Historical Decomposition

It is not unreasonable to expect that the large explanatory power of financial shocks on the GFC factor largely comes from periods of financial distress. Perhaps the relative importance of U.S. monetary policy shocks and GZ shocks is different across sub-periods. To evaluate how our shocks contribute to movements in the GFC factor over time, we conduct an historical decomposition (HD) of our baseline VAR. A standard historical decomposition of the vector $\boldsymbol{y}_t$ in Equation (1) shows that the variables are linear combinations of the history of the structural shocks $\boldsymbol{\epsilon}_{it}$ and an exogenous component referred to as the "baseline projection". In an historical decomposition, summing up the contribution of all the shocks at any time t (together with the baseline projection) recovers the original time series at time t. The HDC of the GFC factor in our model can thus be thought of as a counterfactual: what would have been its dynamics were only shock i to have occurred?

We display the results of the historical decomposition in Figure 5. We display the GFC factor itself along with the contributions to its movements coming from (i) the GZ shock, (ii) the U.S. monetary policy shock, and (iii) all other shocks combined. As seen in the figure, GZ shocks are the dominant influence in almost all sub-periods, the main exceptions being the Volcker disinflation and the mid-1990s.[13] Furthermore, periods when financial shocks explain a greater proportion of the global financial cycle tend to coincide with—or presage—market downturns. This includes the 1987 stock market crash, the turmoil in Russia and Asia in 1998, and particularly during the 2008 financial crisis. The GZ shock tends to run counter to the global financial cycle during boom times, except for the Great Moderation period, during which all financial and economic shocks display great bullishness. On the other hand, the GZ shock tracks the GFC factor closely during distressed times. This suggests a potential early warning role of credit variables on crisis events.

[13] In an HD exercise designed to assess the importance of U.S. monetary policy shocks for U.S. output over different time periods, Baumeister & Hamilton (2018) conclude that these shocks were not the dominant influence during the Great Moderation.

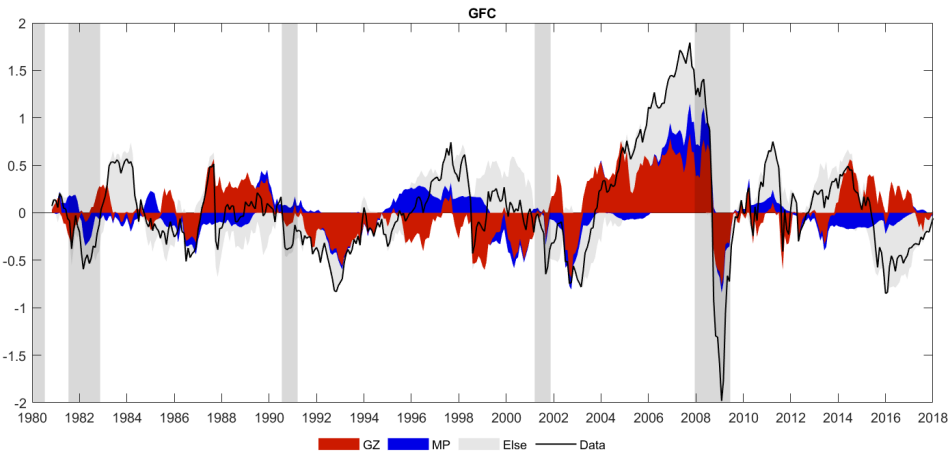


Figure 5: HB-SVAR Historical Decomposition: Global Financial Cycle on Financial Shocks

Note: Historical decomposition of GFC, contributions of shocks to GZ, FFR, and others in a Wold representation. The actual GFC data series is the black line. NBER recessions are shaded in grey.

3.5 Alternative Identification Approaches: SV-SVAR and Proxy SVAR

3.5.1 Stochastic Volatility SVAR identification

Our first robustness check on the baseline Brunnermeier et al. (2021) framework for identification also allows us to estimate the effects of multiple shocks without having to rely on timing or sign restrictions. Bertsche & Braun (2022) show that SVARs can be identified by exploiting stochastic volatility. They argue that compared to the heteroskedasticity-based SVAR, the SV-SVAR performs better in identifying the structural parameters especially when the variance process is misspecified.

Following Bertsche & Braun (2022), we specify our SVAR reduced form error u_t as,

$$u_t = C_0^{-1}\epsilon_t = C_0^{-1}V_t^{1/2}\eta_t. \tag{6}$$

where η_t is assumed to be a white noise error.

The volatility of structural shocks thus are captured by $V_t^{1/2}$. If only $r \leq n$ structural shocks are heteroskedastic, we may specify V_t as follows,

$$V_t = \begin{bmatrix} diag(exp(h_{1t}), ..., exp(h_{rt}) & 0 \\ 0 & I_{n-r} \end{bmatrix}. \tag{7}$$

$$h_{it} = \phi_i h_{i,t-1} + \sqrt{s_i}\omega_{it}, for i = 1, ..., r. \tag{8}$$

where ω_{it} is normally distributed with a mean of 0 and a standard deviation of 1, and is uncorrelated with structural shocks. Bertsche & Braun (2022) show that under some mild assumptions, SV-SVAR model (1), (6), (7), and (8) can be identified up to permutations and sign changes.[14]

Figure A1 displays the impulse responses from a model with the same baseline set of variables but now using the SV-SVAR identification of shocks. U.S. monetary policy shocks generate similar impulse responses as in the HB-SVAR model. A surprise tightening leads to a large drop in IP, TS, GFC, LEVUS, and global IP, while the response of GZ is insignificant. Positive shocks to LEVUS lead to a rise in GZ spreads, small declines in IP, TS, and GFC, while boosting global IP. Large effects come from GZ shocks: the GFC factor declines substantially and immediately, U.S. and global IP fall in the first year, while leverage, term spreads, and PCE fall slightly. Finally, according to the variance decompositions displayed in Figure A2, GZ shocks are again the primary driver of the global financial cycle factor, accounting for half of the forecast error variance of GFC at short horizons, while U.S. monetary policy shocks do not account for a significant fraction.

3.5.2 Proxy SVARs

The results above speak clearly to the main issue posed by this paper. We have found that although U.S. monetary policy shocks play some role in explaining the global price factor, the effects of (orthogonal) financial shocks are significantly greater. We have shown that this result, derived using shocks estimated through a time-varying volatility approach, is robust to several changes in specification. However, although our U.S. monetary policy shocks generally have reasonable properties, the shocks also have delayed effects on the global price factor. In contrast, the monetary shocks identified by Miranda-Agrippino & Rey (2020b) using a proxy SVAR—their only identified shock—generate immediate responses of the factor. It is thus reasonable to ask whether our baseline results are comparable to those derived using a proxy SVAR approach. We show next that they are.

Many applications of proxy SVARs, including Gertler & Karadi (2015) and Miranda-Agrippino & Rey (2020b) set out to identify only the U.S. monetary policy shocks. Because our goal is to compare the relative importance of this shock to others, we must extend their approaches.

We proceed in two ways. First, we extract GZ shocks from our baseline HB-SVAR model and feed them into a proxy SVAR model similar to Miranda-Agrippino & Rey (2020b), which includes variables such as FFR, industrial production, PCE, term spread, commodity price, GZ index, the

[14] According to the ARCH tests (part of the "mild assumptions") in Table A1, the PCM residuals do not exhibit significant heteroscedasticity, so that variable is excluded. We also drop LEVEU to facilitate presentation; results of the 9-variable SV-SVAR model with LEVEU are similar.

GFC factor, US leverage, EU leverage, and global industrial production excluding the US (column 3 in Table 3). Second, we replace the FFR in our baseline HB-SVAR and SV-SVAR models with an "IV predicted FFR". This construct is the fitted FFR from regressing FFR on monetary policy IVs (the high-frequency monetary policy surprises used prominently in the literature). In this way, we incorporate into our baseline estimation information from monetary policy IVs as in Gertler & Karadi (2015) and Miranda-Agrippino & Rey (2020b).

Approach 1 For a proxy SVAR, we can write the general structural form of equation 1 as,

$$\boldsymbol{y}_t = \boldsymbol{c}^* + \sum_{j=1}^{p} B_j \boldsymbol{y}_{t-j} + S\boldsymbol{\epsilon}_t, \tag{9}$$

where $S = C_0^{-1}$, a $n \times n$ matrix, characterizes the simultaneous relationship between structural shocks and reduced form innovations. $B_j = C_j C_0^{-1}$ $(j = 1, \ldots, p)$ are $n \times n$ reduced form coefficient matrices, $\boldsymbol{\epsilon}_t$ is the vector of structural shocks.

In order to estimate the effects of monetary shocks, we do not need to identify all coefficients of S. We only need to identify s_1 the first column of S. Without loss of generality, we assume the monetary shock ϵ_t^p to be the first structural shock. According to Mertens & Ravn (2013) and Gertler & Karadi (2015), we can use an external instrumental variable z_t to identify s_1. The IV needs to satisfy the following two conditions: (1) $E[z_t \epsilon_t^p] \neq 0$; and (2) $E[z_t \epsilon_t^{np}] = 0$, where ϵ_t^{np} is a nonmonetary structural shock. Specifically, the IV has to be relevant for monetary shocks, and their correlation has to be nonzero. It also has to be exogenous such that it has no correlation with structural shocks other than monetary shocks. Similarly, when we want to identify the effects of GZ shocks, we need to find an IV for GZ shocks such that the IV is relevant for GZ shocks, and does not correlate with any other shocks (including monetary shocks).

Figure 6 presents impulse responses and FEVDs of the global price factor. To further save space, we restrict attention to the GZ shocks and monetary policy shocks. The first two columns present results for the GZ shocks while the remaining columns depict the effects of U.S. monetary policy shocks. We investigate three IV-derived monetary policy shocks: the FF4 and Romer-Romer (2004) shocks, both used by Miranda-Agrippino & Rey (2020b), and the monetary instrumental variables used in Miranda-Agrippino & Ricco (2021)). The solid lines denote median estimates using Bayesian proxy SVARs, while the dotted lines denote results using frequentist proxy SVARs.

Following Stock et al. (2012), we estimate using one instrument at a time.[15]

As indicated by the panels in the top row, the GFC factor immediately responds negatively and significantly to both GZ shocks and U.S. monetary policy shocks. The responses to GZ are also persistent. Results using GZ shocks are robust across cases. Results are less robust with respect to the alternative constructions of the monetary policy shock. For these, responses to Romer and Romer shocks are not large.[16] Thus, even within the same proxy SVAR setting, GZ shocks still have a much larger and more robust effect on the global price factor than the monetary policy shocks. As seen in the bottom row, the GZ shock also explains a much larger share of the forecast error variance of the global factor than do U.S. monetary policy shocks.

Approach 2 As noted above, in our second approach we replace the FFR in our baseline volatility-based identification models with the fitted FFR from regressing it on the monetary policy IVs used above and elsewhere in the literature. In Figures A9 to A12 we show the impulse responses and FEVDs of our HB-SVAR and SV-SVAR models with the IV-predicted FFR in place of FFR itself. We see a significant immediate effect of the U.S. monetary policy shock on the global factor in this case. All other results are similar to those of the baseline model, including especially that the GZ spread still explains the largest share of the global factor's error variance.

[15] Mertens & Ravn (2013) show that instrumental variables provide sufficient information to identify SVAR models if we try to identify one shock at a time. This allows us to sidestep imposing additional restrictions to simultaneously identify multiple shocks. It should also be noted that, in order to avoid potential correlation between GZ shocks and monetary policy shocks, we find that results are robust even when our GZ shocks are orthgonalized to FF4 before being used as the IV in the proxy SVAR.

[16] Given the more-limited availability of the monetary policy shock IV series, the estimation is run from 1/1980 to 12/2007 in when using Romer and Romer shocks and from 4/1990 to 4/2019 in the cases with FF4 and MPI.

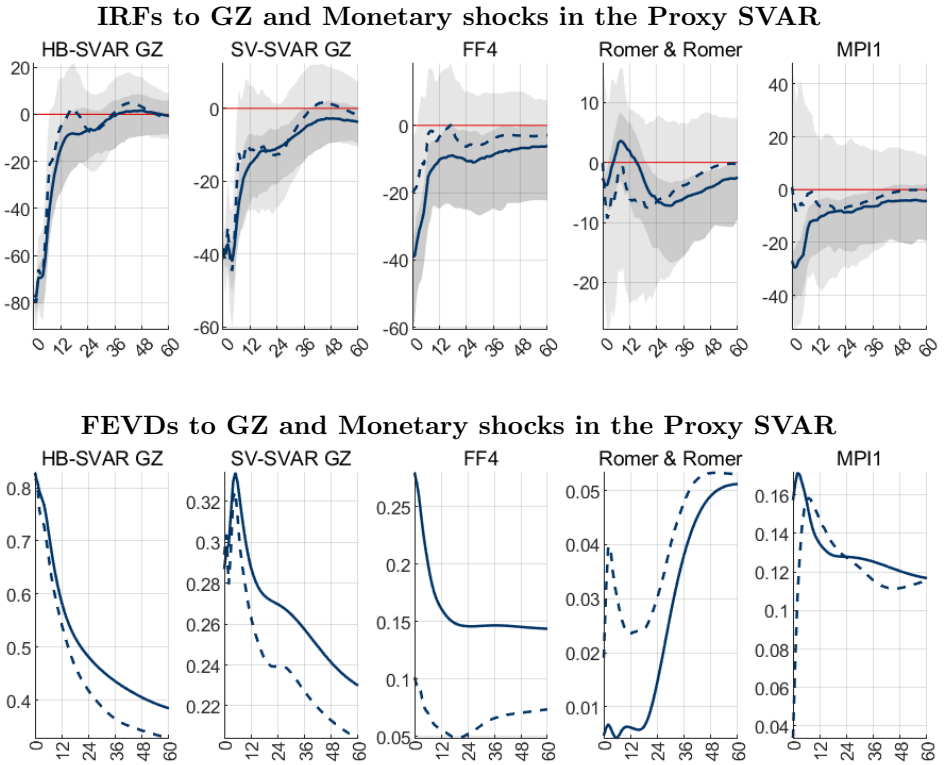


Figure 6: IRFs and FEVDs of the Global Price Factor

Note: Impulse responses and variance decompositions are estimated within a proxy SVAR with different IVs. The first two columns in the first row show impulse responses of the global price factor to the GZ structural shocks extracted from our HB-SVAR and SV-SVAR models, with 68 percent (dark grey) and 90 percent (light grey) confidence intervals. Columns 3-5 in the first row show impulse responses of the global price factor to several monetary policy shocks: FF4, Romer and Romer (2004), and the instrumental variable used in Miranda-Agrippino and Rico (2021). The second row shows the corresponding variance decompositions of the global price factor.

Relative IV-identified shock variances In Table 6, we display the variances of the GZ and U.S. monetary policy shocks identified using the instrumental variables procedure described above. For the sake of comparison with our baseline findings, we compute the shock variances over the regime sub-periods used in the baseline estimation. The first five rows of the table correspond to one of the five estimates displayed in Figure 6, left to right. There is considerable time-variation in the variances of these shocks under the proxy SVAR approach (lending credence to a heteroscedasticiy-based model). The bottom two rows of the table are repeated from Table 4, the shock variances from our baseline BPSS model. We display them for the sake of comparison. As seen in the table, both the baseline procedure and the proxy SVAR approach give rise to the same pattern of (time-varying) shock volatility across sub-periods. GZ (monetary policy) shocks are relatively large in the 2008-10 (1980-82) sub-period. On the other hand, monetary policy (GZ) shocks are relatively small during the Great Moderation (entire 1980's)

Table 6: Relative IV-identified Shock Variances

Shock	Jan 1980-Dec 1982	Jan 1983-Dec 1989	Jan 1990-Dec 2007	Jan 2008-Dec 2010	Jan 2011-Dec 2015	Jan 2016-Apr 2019
HB-SVAR GZ	0.42	0.54	0.73	4.21	1.23	0.70
SV-SVAR GZ	0.50	0.59	0.69	5.24	0.70	0.55
FF4 (Monetary)	-	-	1.11	1.60	0.47	0.50
Romer & Romer (Monetary)	8.25	0.68	0.29	-	-	-
MPI (Monetary)	-	-	0.96	1.52	0.55	1.20
GZ (baseline)	0.18	0.34	0.64	3.28	1.03	0.57
FFR (baseline)	4.76	0.96	0.12	0.13	0.01	0.04

Note: Estimates in the top five rows are based on the proxy SVAR depicted in Table 3 and their corresponding IVs. The bottom two rows are repeated from Table 4, the shock variances from our baseline BPSS model.

3.6 The Role of Floaters

An important finding of Miranda-Agrippino & Rey (2020b) (section 3.2.3) is that countries who adopt a floating exchange rate regime are as equally exposed to U.S. monetary policy shocks as other countries. They reach this conclusion by restricting the sample to include only "independently floating" countries, using the IMF's de-facto classification.[17] Their impulse responses indicate that the magnitude of the contraction in credit variables is very similar to that obtained using the full sample of countries.[18] We conduct a similar investigation, beginning by constructing a GFC index for the countries designated by Miranda-Agrippino & Rey (2020a) as independently floating.[19] For simplicity, and noting that the global factor is constructed mostly from global equity prices, we use as a proxy an equal-weighted MSCI stock price index for these countries, without incorporating other risky asset prices as would be done with a full reconstruction of the GFC factor.

Full sample of countries Because we focus more narrowly on global stock prices, we first show that our baseline findings—with all countries lumped together—are robust to using the MSCI global index in place of the Miranda-Agrippino & Rey (2020b) GFC factor. As indicated in Figure A13, the responses of the MSCI largely mimic those of the GFC factor seen in sections 3.1 and 3.2. Figure A14 shows the variance decompositions with the MSCI index in place of the GFC factor. Comparing columns 5 and 6, our conclusions from the baseline SVAR are robust. Shocks to the Gilchrist &

[17] https://www.imf.org/external/np/mfd/er/2008/eng/0408.htm.

[18] As the authors note, their results do not imply that exchange rate regimes are equivalent, but rather that "a floating exchange rate regime is not successful in providing a protective shield against U.S. monetary policy shocks, and that fluctuations in the Global Financial Cycle can affect in a significant way all countries."

[19] Australia, Austria, Belgium, Brazil, Canada, Chile, Cyprus, Czech Republic, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Luxembourg, Malta, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovenia, South Africa, Spain, Sweden, Turkey, and the UK.

Zakrajšek (2012) U.S. corporate bond spread account for about 60-70% of variance in the short run and about 40% at the 2-3 year horizon. Shocks to U.S. monetary policy shocks account for only about 20% of the GFC factor in the long run and considerably less in the short run.

Floaters only We depict the full set of impulse responses and variance decompositions for the SVARs with only floaters in Figure A15 and Figure A16. Following a positive GZ shock, MSCI(floaters) exhibits a similar pattern to those with MSCI(full sample) *but the magnitude is smaller*. The same is true for a tightening monetary policy shock. In Figure 7, we hone in on the contrast between the variance decompositions of MSCI (full sample) and MSCI (floaters). We see that the variance shares explained by the GZ shocks and FFR shocks decline significantly for the sample of independently floating countries. Thus, although a floating exchange rate regime does not completely insulate countries from external shocks like GZ shocks or U.S. monetary policy shocks, it does so partially.

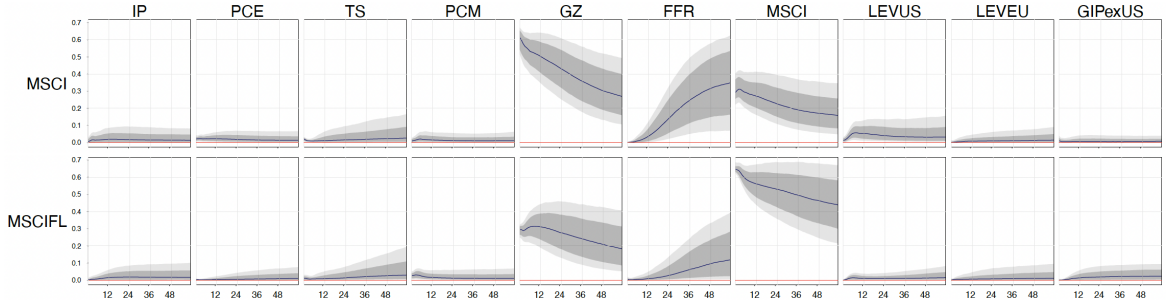


Figure 7: Variance Decomposition: MSCI (Full sample) vs. MSCI (Floaters)

3.7 Further Robustness Checks

We conduct many other extensions and robustness checks, in order to validate our main findings comparing the effects of U.S. monetary policy shocks and shocks to the GZ spread. First, we replace GZ spreads with the excess bond premium—a measure of US credit market sentiment computed from deviations of corporate bond prices relative to the measured default risk (Gilchrist and Zakrajšek (2012)). We report the impulse responses and variance decomposition results in Figure A17 and Figure A18. The results with the EBP are quite similar to the results of baseline model. As mentioned by Gilchrist & Zakrajšek (2012), Gilchrist et al. (2021), the excess bond premium is the residual component orthogonal to default risk in corporate bond spread, and essentially results from a retrenchment of risk-bearing capacity of intermediaries during financial distress. Therefore, the immediate reaction of global asset prices to the EBP shock in Figure A17 points to the significant role of financial institutions in influencing the Global Financial Cycle.

Second, we replace the federal funds rate with the Wu-Xia shadow Fed funds rate. The Fed funds rate was stuck at the zero lower bound during 2008 - 2015, which might invalidate our identification of monetary policy shocks. The Wu-Xia shadow rate can alleviate this concern by exploiting information in the yield curve to back out a flexible short-end interest rate that is not bounded below by zero. In (Appendix) Figure A19 and Figure A20, we find that results are similar to, and a little sharper than, the baseline findings.

Third, we show that our main conclusions are robust to adding to the baseline VAR measures of uncertainty. Akinci et al. (2022) emphasize the role of U.S.-specific uncertainty in explaining movements in key global financial cycle indicators such as international capital flows, risk premia, and asset prices, foreign exchange rates, and deviations from uncovered interest parity. In their model, an exogenous increase in U.S.-specific uncertainty leads to higher risk premia and lower asset values in both countries due to deleveraging pressure on U.S. intermediaries, the dollar appreciates, capital flows out of the foreign country, and the foreign currency excess return increases.[20] In Figure A21 and A23, we present the impulse responses of the model with world uncertainty index (WUI) as in Ahir et al. (2022) and financial uncertainty (TFU) as in Ludvigson et al. (2021). There is a gradual decline of the GFC factor following a shock to WUI and TFU. The depressing effect of rising uncertainty on U.S. banking leverage global IP is quite persistent over time. As seen in variance decompositions of Figure A22 and A24, our baseline conclusions on the relative importance of different shocks are robust.

Fourth, we investigate distinctions between the roles of credit aggregates and credit spreads, which represent the quantity and the price of credit respectively. A version of the ten-variable model including U.S. domestic credit aggregates and U.S. business credit and household credit can be found in Appendix section G (see Figure A25 to Figure A28). The results show clearly that the effect of credit aggregates is dominated by the credit spread shock.

Fifth, we include several other variables in our SVAR models alternatively to check robustness. We explore further the role of (1) global risk aversion estimated by Miranda-Agrippino & Rey (2020b), (2) USD exchange rate, (3) global domestic credit and global capital inflows. Results are reported in Figure A29 to Figure A36. Our conclusions regarding the effects of GZ spreads and its relative importance in driving the GFC factor are confirmed.

[20] They propose a two-country dynamic macro model, featuring balance-sheet constrained financial intermediaries. The main exogenous driving force in the model is a shock to the standard deviation of the future productivity of U.S. physical capital which generates time variation in uncertainty about intermediaries' future returns. This is akin to the modeling of uncertainty in Basu & Bundick (2017)).

Finally, we conduct a robustness check of the baseline model by excluding the key variable - the GZ index. Does this restore the primacy of U.S. monetary policy shocks in explaining the GFC factor? The impulse responses and FEVDs are reported in Figure A37 and Figure A38, respectively. Impulse responses are quite similar to the baseline results for all other variables. More interestingly, we find that most of the forecast error variance of GFC is left unexplained (explained only by itself) if we exclude the GZ index from the SVAR model, suggesting that the significant role of GZ can not be replaced by other variables.

4 Discussion and Conclusions

4.1 New thoughts on interpretations – notes for ourselves in Sept 2023

In GZ's 2012 AER, GZ is interpreted as a timely and useful gauge of credit supply conditions, which then contains predictive information about economic activities via the financial accelerator mechanism. That is, a contraction in credit supply — implied by increases in GZ — causes a drop in asset prices and a contraction in economic activity.

What's in GZ that reflects credit supply conditions? One primary factor is financial intermediary risk aversion and the other is their balance sheet conditions.

With the current set of results, one direction we can potential push towards is to argue that, it is the balance sheet condition of US intermediaries that predominantly drive GFC, just as evidenced by the 2008 global financial crisis.

It's the part of GZ that contains information about the degree of strains in the financial sector — going beyond movements in effective risk aversion — that moves the global financial markets /triggers movements in the GFC factor .

To go deeper in substantiating this argument, we could incorporate the following data in one way or another in our VAR: 1) credit standards data from SOOLOS, 2) aggregated profitability / asset holding data including ROA etc 3) financial institutions CDS spread. All follow GZ's original AER, section IV (C).

Re: Nancy's point on differentiating contributions from her paper on equity markets, there is a key difference she is overlooking. Because of the inherent asymmetric nature of debt contracts and their payoffs, our results — especially if we still have our results after incorporating whatever

measure they use on equity markets— reflect the fact that corporate bond prices are better able to capture downside risks

Another potential angle is that credit spreads can incorporate investors' expectations of future corporate defaults, which in turn affect corporate sector profits, employment, investment, among other factors that might be linked to global financial cycle movements

1. I think we want to include the specification with Bo's new risk variable in the *baseline*.

2. Per one (both?) of the referee criticisms, let's present the full set of irf and VDC figures only for the baseline case. Perhaps for one additional robustness case, but that's it.

3. Utilize *one table* to present VDC results for all of the robustness tests. Choose four or five horizons: impact and months 6, 12, 24, 36.

4. Present VDCs of key series: GFC obviously and then GZ and I don't know, FFR (or other monetary policy indicator), Risk, Lev.

5. We need to add some robustness checks, in particular those that include ECB monetary policy shocks. Perhaps other central banks too, even China (Sylvia has work on this).

6. will look into the Kilian critique of identification through heteroskedasticity that Sylvia notes a couple of times in her report? Seems like we should get on top of this issue. We can simply state all the assumptions (as we do now) and say things like "here are the shortcomings of BPSS/IDH" while making the case that these shortcomings are much less than those of alternatives like sign restrictions. Again, we do some of this already but still got criticized pretty strongly.

An important literature emphasizes the role of Fed monetary policy in driving the global financial cycle, captured by a unique indicator—the global factor— extracted from comovements of risky asset prices worldwide. Is U.S. monetary policy the main driver of the global financial cycle? Miranda-Agrippino & Rey (2020b) show that U.S. monetary policy shocks induce comovements in the international financial variables that characterize the global financial cycle. Miranda-Agrippino et al. (2020) and Miranda-Agrippino & Rey (2020a) provide additional evidence that Fed monetary policy plays the key role in driving the global financial cycle. In this paper, we ask the following questions: what is the economic significance of other shocks in addition to U.S. monetary policy? Can there be another key barometer in accounting for strains in the global financial system?

We initiate a first attempt to rank a large number of shocks in their contributions to driving the global financial cycle, estimating a medium-to-large structural VAR model with a heteroskedasticity-

based identification. From this, we provide a clear ranking of contributions of various economic forces to the global financial cycle. Critically, we show that U.S. corporate bond spreads—especially, the excess bond premium that reflects the pricing of defaults rather than their risk—emerges as the most powerful driver of the global financial cycle. By comparison, contributions of Fed monetary policy shocks to global financial cycles appear moderate, consistent with monetary policy being *reactive* to changes in underlying economic and financial conditions. Our results suggest that the hegemon of the U.S. in the global financial system may be rooted in the centrality of U.S. financial intermediaries and the dollar rather than the Fed itself. This conclusion is consistent with—and indeed reflective of—the following features of the global financial landscape.

Dollar dominance The cost and availability of U.S. dollar funding can shift drastically as the risk-bearing capacity of U.S. intermediaries—measured by U.S. GZ spreads—fluctuates, creating a channel for propagation and amplification of credit shocks originating in U.S. funding markets. The international financial and monetary system that emerged after World War II has been defined by the centrality of the dollar, the world's reserve currency and most widely used for payments and investments. Global preeminence of the dollar has been supported by the depth and liquidity of U.S. financial markets, the size and strength of the U.S. economy, its stability and openness to trade and capital flows, and trust in U.S. institutions and the rule of law. By most measures the dollar plays an outsized international role relative to the U.S. share of global GDP. Dollar dominance has been also highlighted in its wide use as a medium of exchange in international banking and financial transactions, as well as an exceedingly high share in foreign exchange transactions. Bertaut et al. (2021) show that about 60 percent of international and foreign currency liabilities (primarily deposits) and claims (primarily loans) are denominated in U.S. dollars. This share has remained relatively stable since 2000 and is well above the euro's share (about 20%).

This broad international use of the U.S. dollar generates significant benefits globally, arising from economies of scale and network effects, which reduce the costs of transferring capital and risks around the financial system. However, the resulting interconnectedness can transmit and amplify shocks that emanate from the United States across the globe. The large footprint of U.S. dollar funding activity in international financial markets becomes especially salient during times of stress. With dollar financing in high demand during times of crisis, foreign financial institutions may face difficulties obtaining dollar funding. For example, U.S. dollar funding stresses faced by non-U.S. entities during the 2008 global financial crisis and 2010 European debt crisis, contributed to their

spread across the globe. U.S. dollar funding proved to be fragile during the 2008 crisis: Global banks had to roll over increasingly large amounts of their funding at shorter maturities even though they had relatively long maturity assets. Hence, their maturity mismatch worsened considerably. Some European banks with low ratings lost access to U.S. dollar funding and were forced to finance their dollar assets by tapping the foreign exchange swap market, further propagating financial stress through this market (Baba & Packer (2009)). Fragility of this U.S. dollar funding was laid bare once again during the euro area sovereign debt crisis. When vulnerabilities emerged in the European sovereign debt market in 2010, U.S. money market funds—the usual counterparties of European banks—were concerned about the credit risk of European banks and decided to quickly rebalance their portfolios toward other counterparties or to lend, but only at very short maturities.

U.S. centrality in the global financial network Recent financial crises, often attributed in part to contagion emanating from pervasive entanglements among financial institutions, has rekindled interest in the role of financial interlinkages and networks as a shock propagation and amplification mechanism. Models of financial interactions studied in several papers (e.g., Allen & Gale (2000), Battiston et al. (2012), Elliott et al. (2014), Cabrales et al. (2014) and Acemoglu et al. (2015)) share commonality at their core. In each, a financial institution's "state", capturing its health or ability to meet its obligations, depends on the state of other financial institutions to which it is connected. Consequently, shocks to a given institution can propagate to others within the economy, potentially snowballing into a systemic crisis. Although such models pertain to a single economy, the central insight can be extended to a global financial network characterized by high interconnectedness through, among other factors, global integration and the dominant international roles of the U.S. dollar. The global financial network is defined by a single, predominant center: the United States. Miranda-Agrippino et al. (2020) show the network graph associated with bilateral exposures through residence-based international portfolio assets. Strikingly, the U.S. and its portfolio links to financial centres dominate the world of financial investment, representing the only pole in the global financial network. This literature suggests that dense interconnections can lead to a spread of an epidemic-like financial contagion, plausibly underlying the predominant role of U.S. investor risk-bearing capacity in driving global financial cycles.

Global nature of risk panics The contribution of U.S. leveraged financial institutions in driving the global financial cycle can also originate from its additional role of a coordination device for shifts in global risk perceptions. Bacchetta & Van Wincoop (2013) show that a weakened fundamental,

such as reductions in the net worth of leveraged financial institutions and their risk-bearing capacity, by becoming a common focal point of attention by investors everywhere, can lead to a widespread *self-fulfilling* increase in risk perceptions globally. In their model, the weaker the fundamental, the larger is the risk panic, although it does not require a large shock to trigger the panic. Positive shocks to excess bond premium, typically accompanied by shrinking balance sheets of U.S. financial institutions, may set off risk panic dynamics that cause financial contagion across countries.[21]

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[21] Krugman (2008) argued that losses of U.S. leveraged institutions imply a sell-off of both U.S. and Foreign assets, which leads to a further drop in asset prices that amplify these effects; foreign leveraged institutions that have exposure to the U.S. subsequently further contribute to transmission abroad.

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Online Appendix (for online publication only)

A Results using the Baseline Model Variables with SV-VAR (Bertsche & Braun (2022)) Identification

Table A1: ARCH Test p-values of the SV-SVAR model

	Lag=1	Lag=2	Lag=3	Lag=4	Lag=6	Lag=12
IP	0.01	0.03	0.03	0.04	0.10	0.41
PCE	0.01	0.01	0.01	0.02	0.00	0.00
TS	0.00	0.00	0.00	0.00	0.00	0.00
GZ	0.02	0.05	0.01	0.02	0.00	0.01
FFR	0.00	0.00	0.00	0.00	0.00	0.00
GFC	0.05	0.13	0.26	0.39	0.45	0.54
LEVUS	0.00	0.00	0.00	0.00	0.00	0.00
GIPexUS	0.00	0.00	0.00	0.00	0.01	0.15

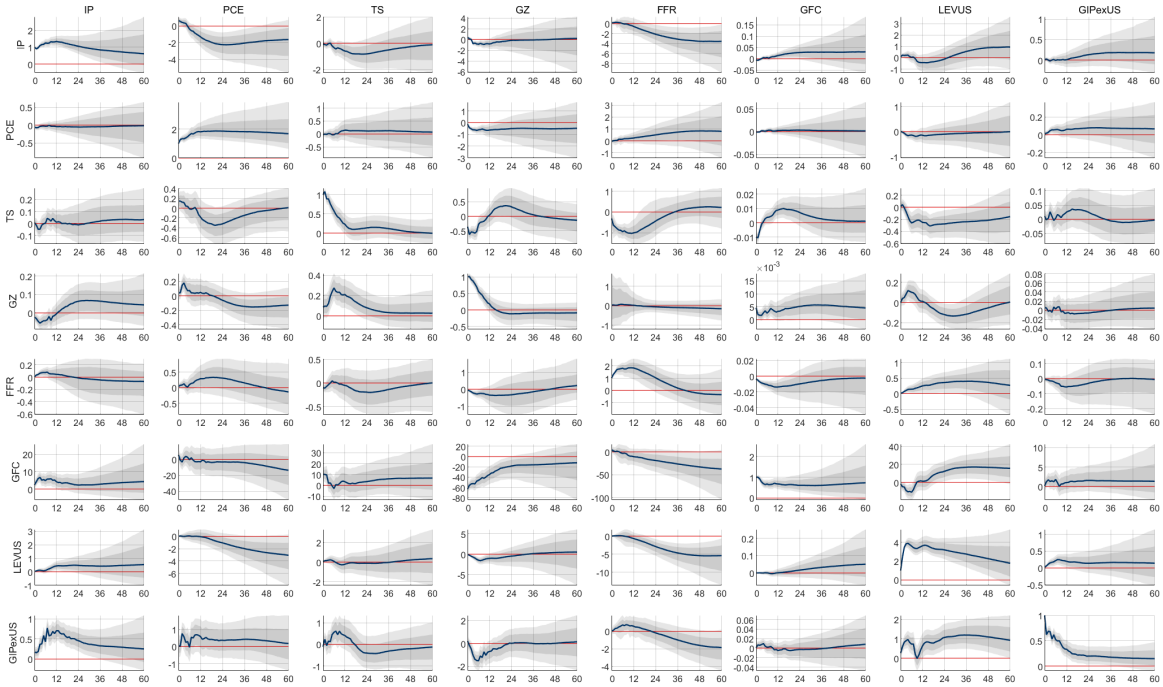


Figure A1: SV-SVAR Impulse Responses: Global VARs, Baseline

Note: Impulse responses of U.S. domestic variables (PCM and LEVEU excluded), and global variables in the baseline model estimated using SV-SVAR, with 68 percent (dark grey) posterior confidence intervals.

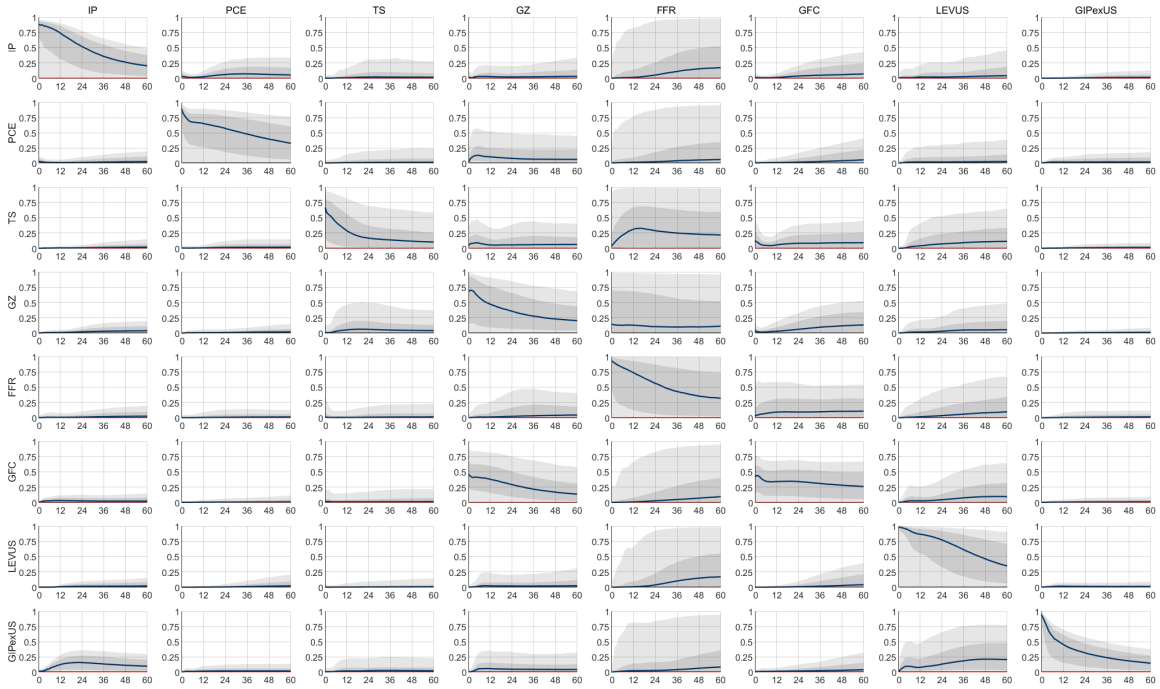


Figure A2: SV-SVAR Variance Decomposition: Global VARs, baseline

Note: Forecast variance decompositions for US domestic variables (PCM and LEVEU excluded), and global variables in model (2) over 60 months, with 68 percent (dark grey) confidence intervals.

B Alternative Regimes, Brunnermeier et al. (2021) Identification

Table A2: Alternative Regime Choices: Global Events

	Start	End	Description
			Global Regime 1
1	Jan 1980	Dec 1982	Great Disinflation
2	Jan 1983	Dec 1996	Great Moderation
3	Jan 1997	Dec 2002	Asian Financial Crisis/LTCM/Dot-com Bubble
4	Jan 2003	Dec 2007	Great Moderation & Pre-crisis
5	Jan 2008	Dec 2015	Financial Crisis and ZLB
6	Jan 2016	Apr 2019	Monetary Normalization
			Global Regime 2
1	Jan 1980	Dec 1982	Early 1980s Recessions
2	Jan 1983	Dec 1989	Recovery from the 1980s recessions
3	Jan 1990	Mar 2000	Great Moderation
4	Apr 2000	Oct 2002	Dot-com Bubble
5	Nov 2002	Dec 2007	Great Moderation & Pre-crisis
6	Jan 2008	Dec 2010	Great Recession
7	Jan 2011	Apr 2019	ZLB; recovery from Great Recession

Estimation using these alternative regimes based on global events is illustrated in Figure A3-A6.

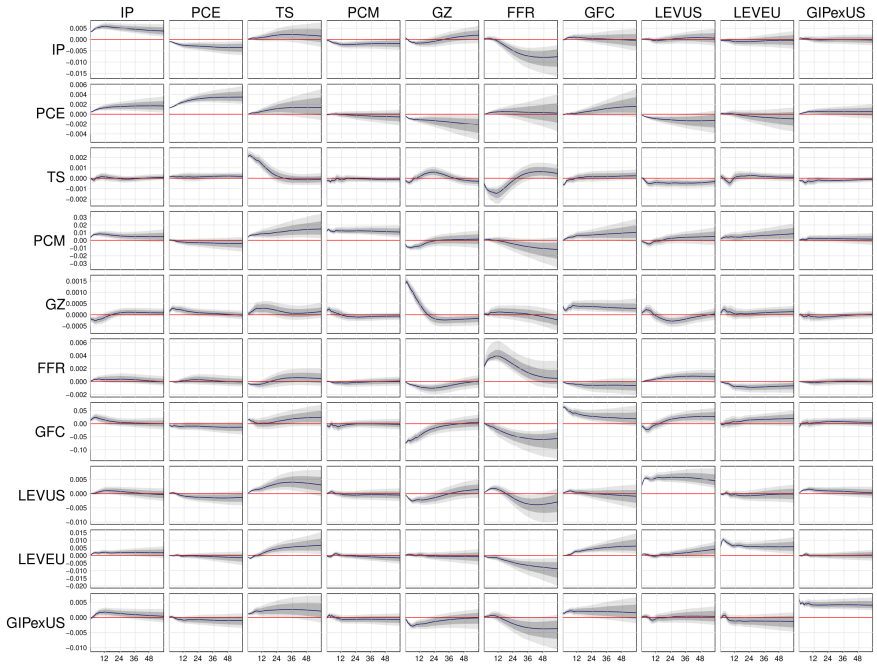


Figure A3: Impulse Responses: Global VARs, Model 1 (Global Regime 1)

Note: Impulse responses to the 10 orthogonal structural shocks using global regime 1 in the baseline model with t-distributed errors over 60 months, with 68 percent (dark grey) and 90 percent (light grey) posterior uncertainty regions. Scaled to an "average" period with unit scale.

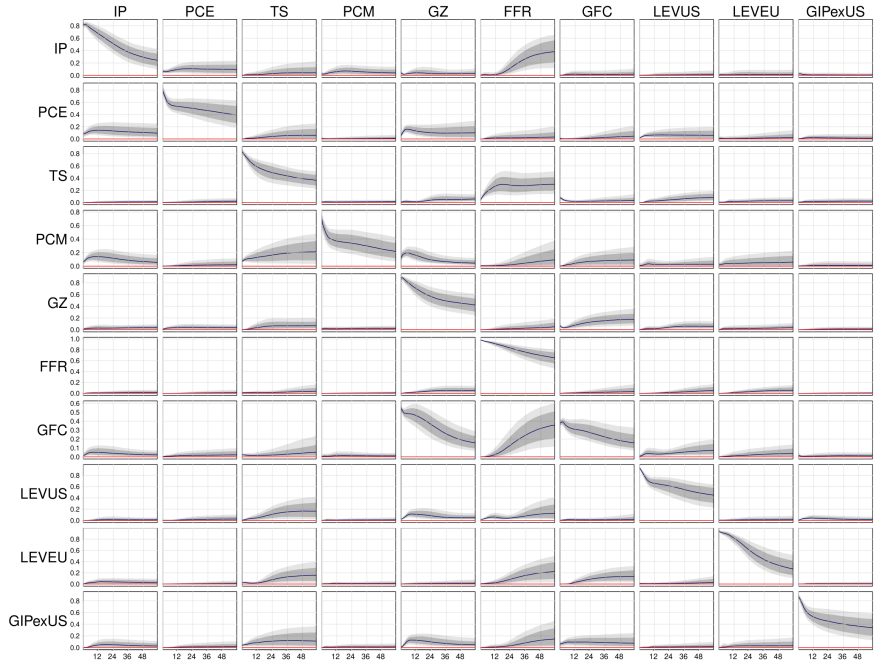


Figure A4: Variance Decomposition: Global VARs, Model 1 (Global Regime 1)

Note: Variance decompositions to the 10 orthogonal structural shocks using global regime 1 in the baseline model with t-distributed errors over 60 months, with 68 percent (dark grey) and 90 percent (light grey) posterior uncertainty regions. Scaled to an "average" period with unit scale.

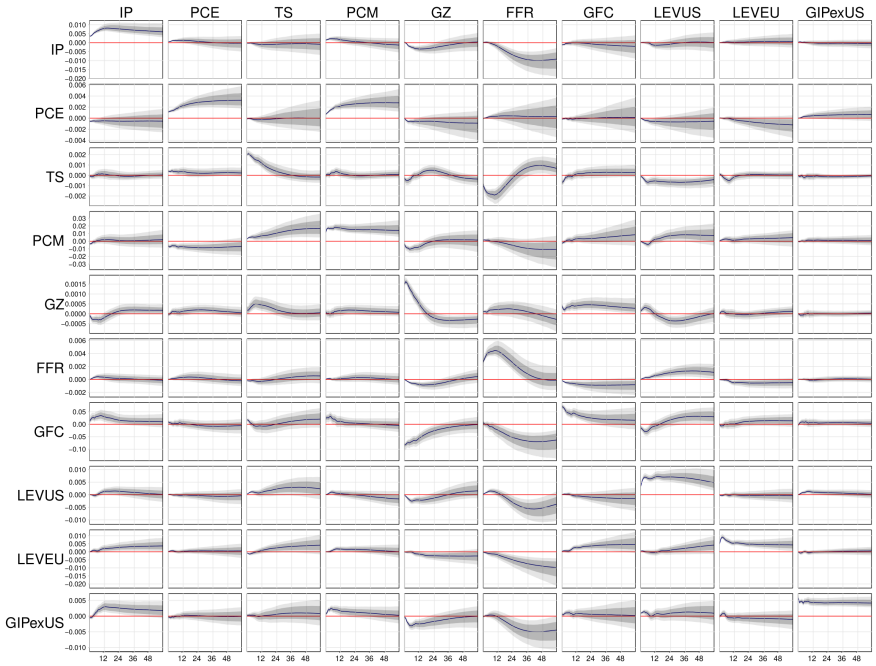


Figure A5: Impulse Responses: Global VARs, Model 1 (Global Regime 2)

Note: Impulse responses to the 10 orthogonal structural shocks using global regime 2 in the baseline model with t-distributed errors over 60 months, with 68 percent (dark grey) and 90 percent (light grey) posterior uncertainty regions. Scaled to an "average" period with unit scale.

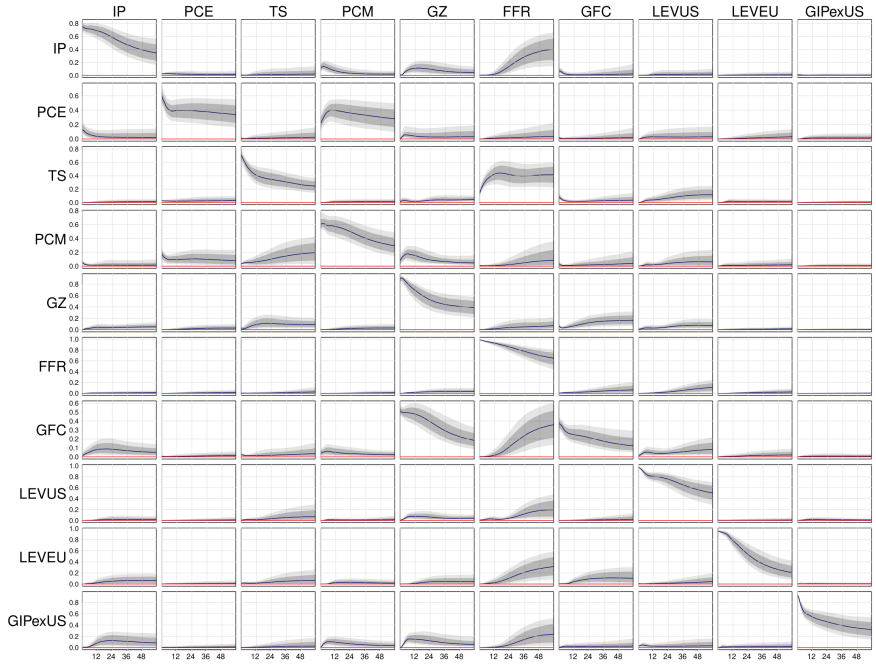


Figure A6: Variance Decomposition: Global VARs, Model 1 (Global Regime 2)

Note: Variance decompositions to the 10 orthogonal structural shocks using global regime 2 in the baseline model with t-distributed errors over 60 months, with 68 percent (dark grey) and 90 percent (light grey) posterior uncertainty regions. Scaled to an "average" period with unit scale.

C Comparison with Proxy SVARs

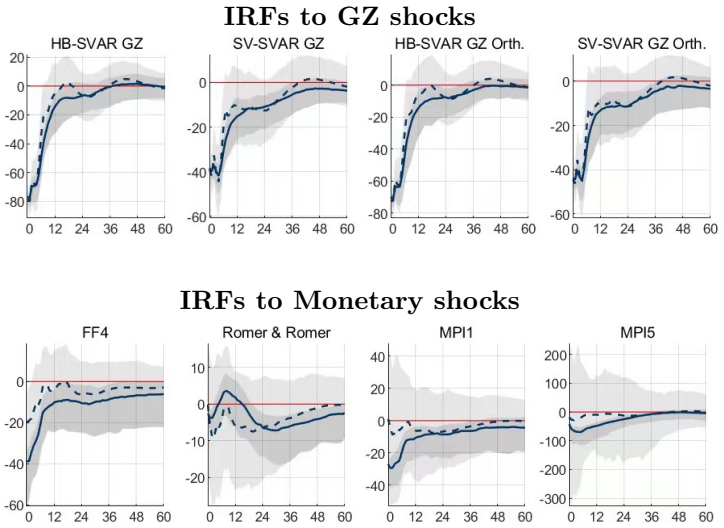


Figure A7: Impulse Responses of the Global Price Factor

Note: Impulse responses are estimated within a proxy SVAR. The first row shows impulse responses of the global price factor to the GZ structural shocks extracted from our HB-SVAR and SV-SVAR models, with 68 percent (dark grey) and 90 percent (light grey) confidence intervals. *Orth.* in the first row (last two columns) denotes that we orthogonalize our GZ shocks with respect to the FF4 shocks. The second row shows impulse responses of the global price factor to several monetary policy shocks, including FF4, Romer and Romer (2004), and two different instruments used in Miranda-Agrippino and Rico (2021).

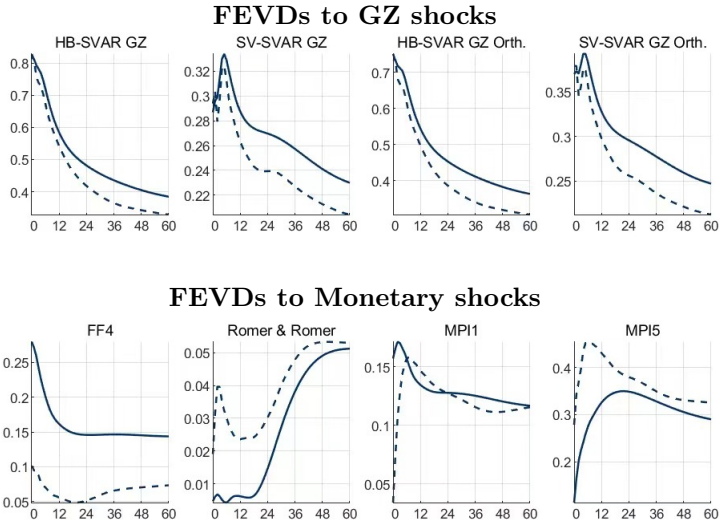


Figure A8: Variance Decompositions of the Global Price Factor

Note: The first row shows variance decompositions of the global price factor to the GZ structural shocks extracted from our HB-SVAR and SV-SVAR models. *Orth.* in the first row denotes that we orthogonalize our GZ shocks with respect to the FF4 shocks. The second row shows variance decompositions of the global price factor to several monetary policy shocks: FF4, Romer and Romer (2004), and two different instruments used in Miranda-Agrippino and Rico (2021).

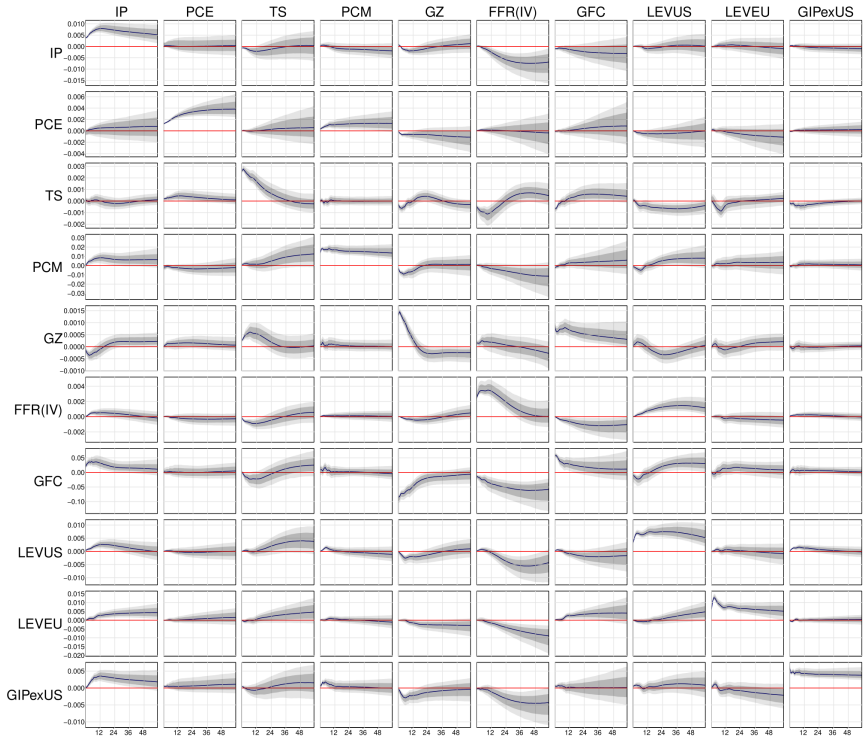


Figure A9: HB-SVAR Impulse Responses (IV): Global VARs

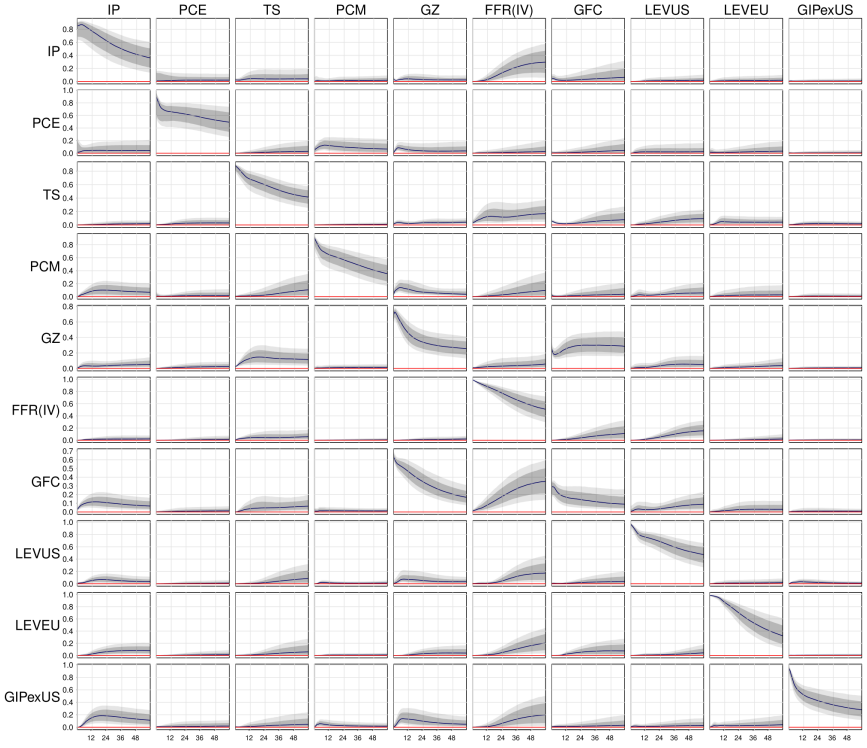


Figure A10: HB-SVAR Variance Decomposition (IV): Global VARs

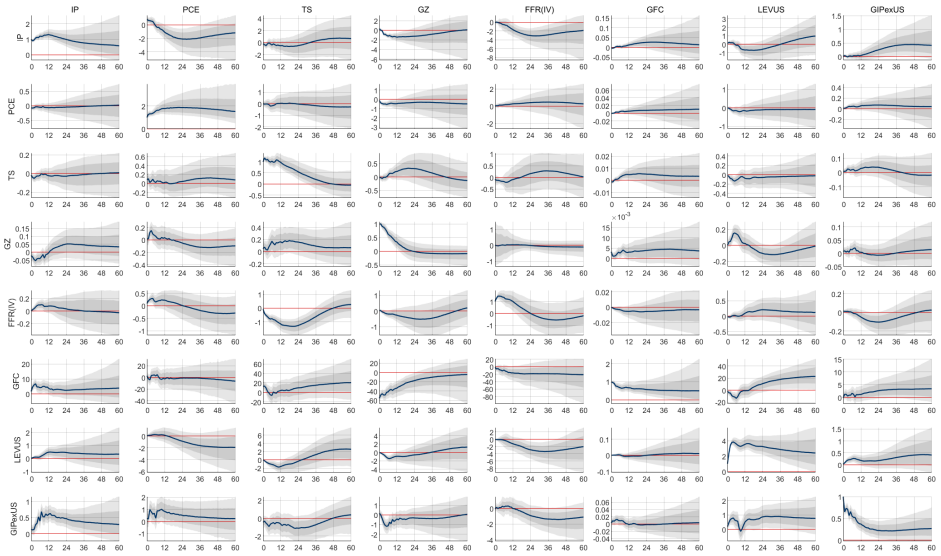


Figure A11: SV-SVAR Impulse Responses (IV): Global VARs

Note: Impulse responses to the 10 orthogonal structural shocks using IV (FF4 and R&R) predicted FFR in place of FFR in the baseline model, with 68 percent (dark grey) and 90 percent (light grey) posterior uncertainty regions. Scaled to an "average" period with unit scale.

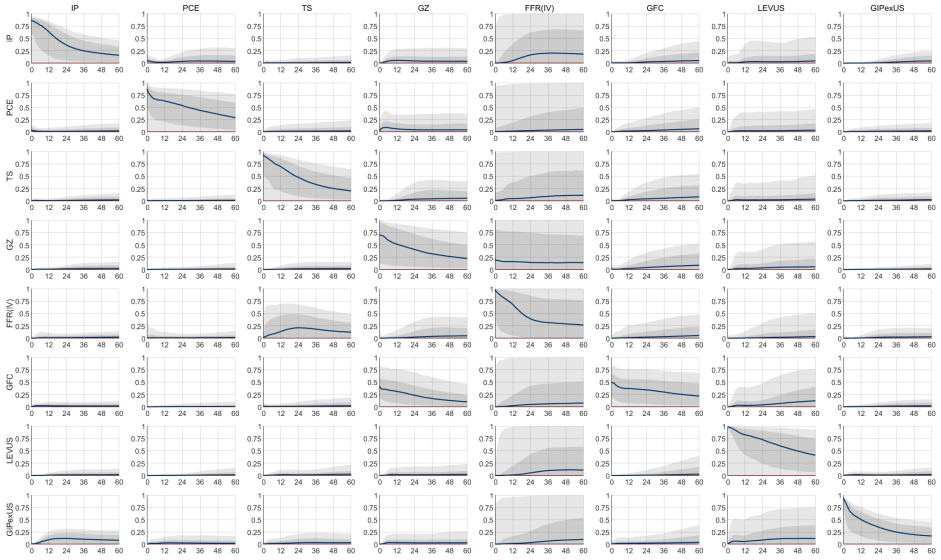


Figure A12: SV-SVAR Variance Decomposition (IV): Global VARs

Note: Variance decompositions to the 10 orthogonal structural shocks using IV (FF4 and R&R) predicted FFR in place of FFR, with 68 percent (dark grey) and 90 percent (light grey) posterior uncertainty regions. Scaled to an "average" period with unit scale.

D The Role of Floaters

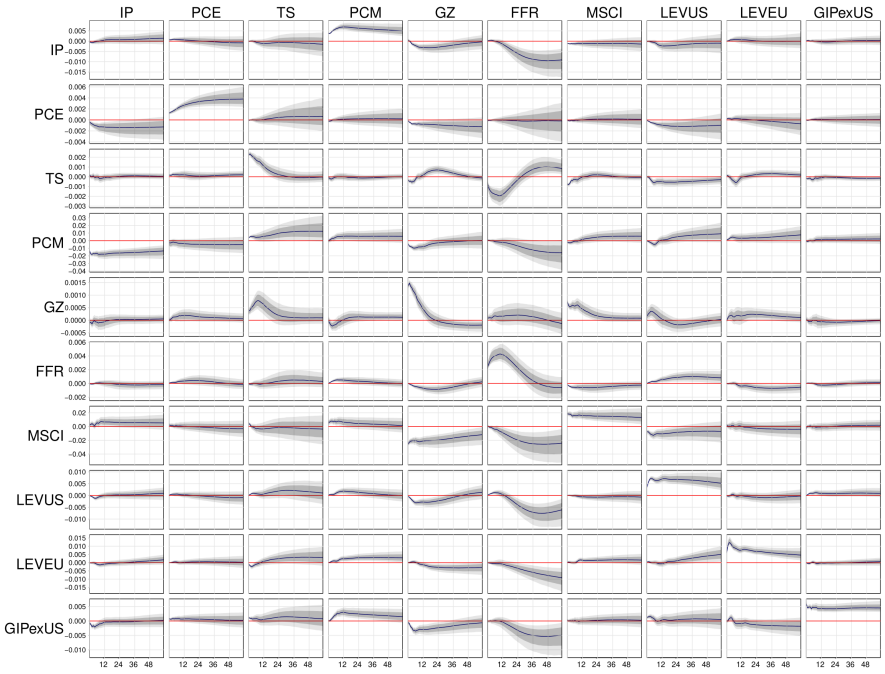


Figure A13: Impulse Responses: MSCI Index in place of GFC factor, full sample of countries

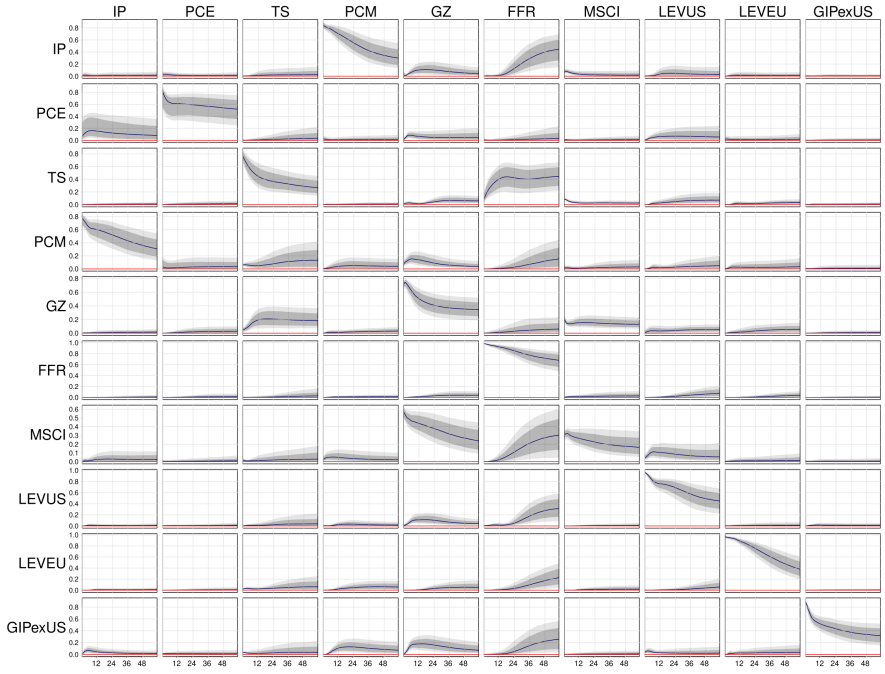


Figure A14: Variance Decompositions: MSCI Index in place of GFC factor, full sample of countries

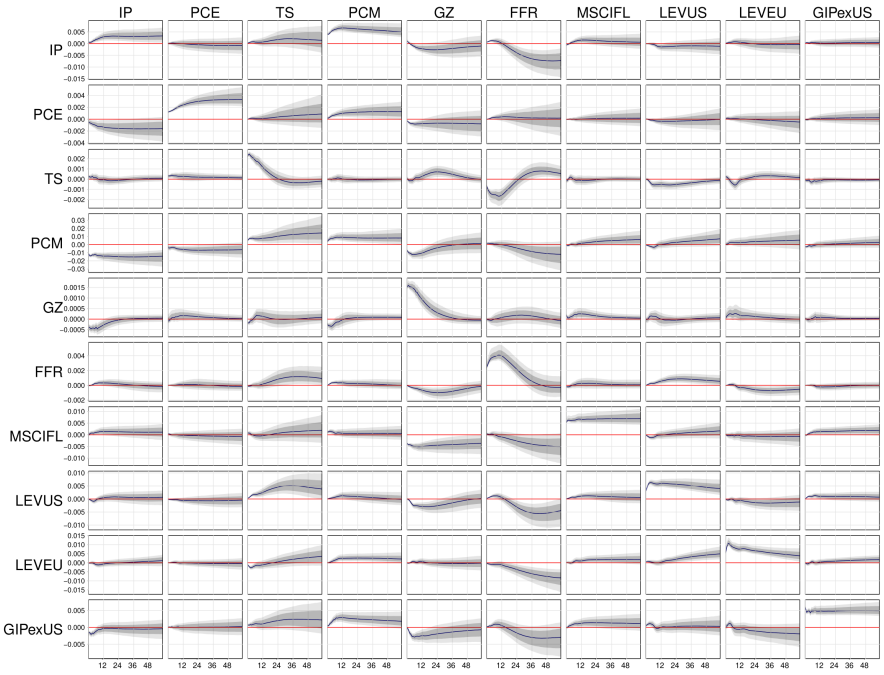


Figure A15: Impulse Responses: MSCI Index for Floaters

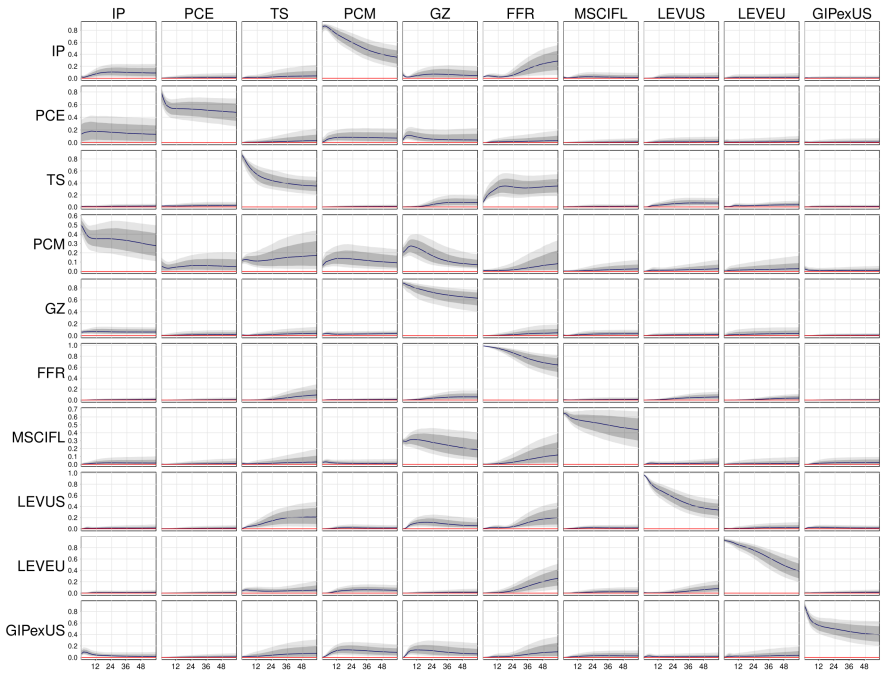


Figure A16: Variance Decomposition: MSCI Index for Floaters

E Excess Bond Premium and the Wu-Xia Shadow rate

In this section we show the results using EBP and Shadow rate for ZLB period, respectively.

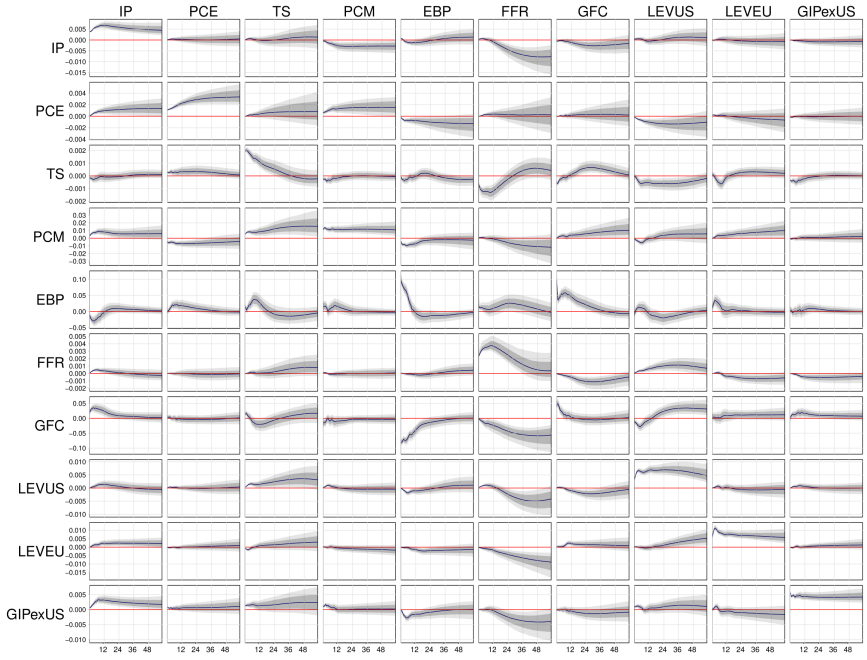


Figure A17: Impulse Response: Global VARs with EBP

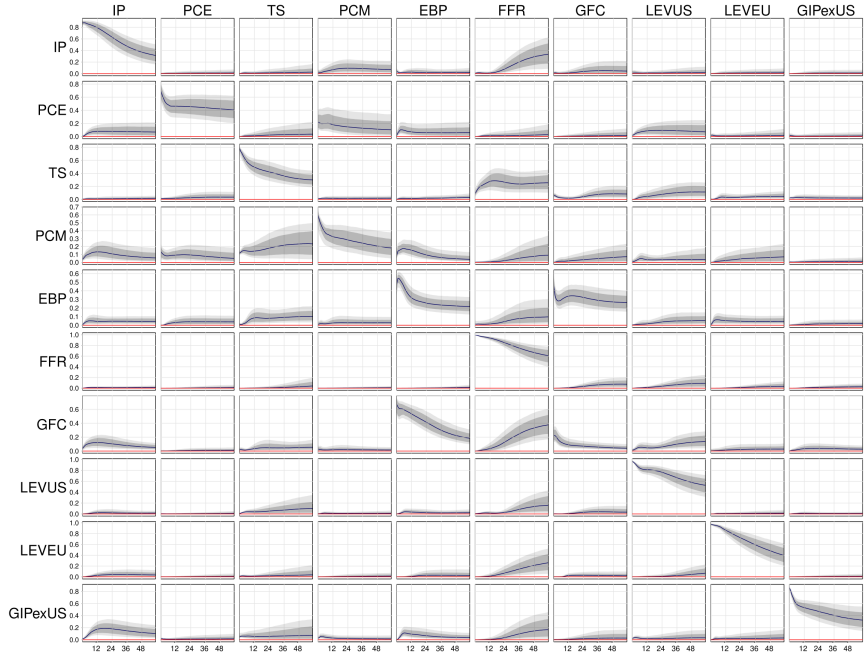


Figure A18: Variance Decomposition: Global VARs with EBP

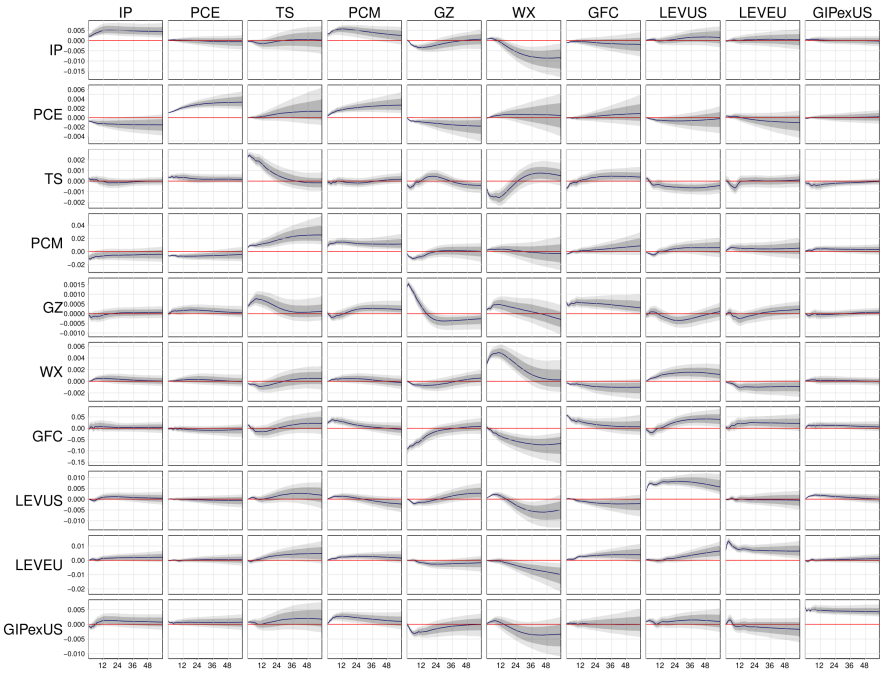


Figure A19: Impulse Response: Global VARs with Shadow Rate

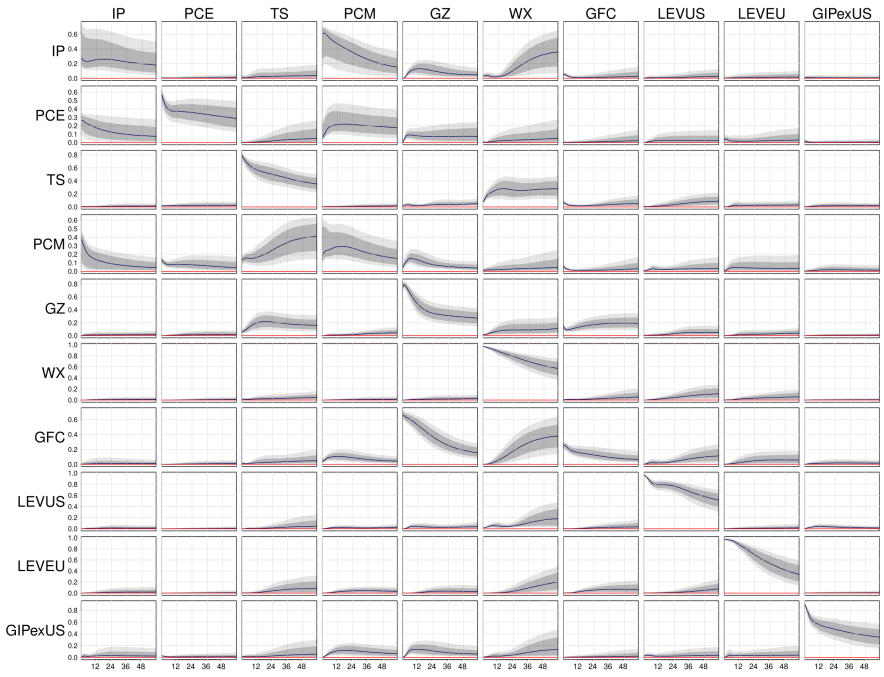


Figure A20: Variance Decomposition: Global VARs with Shadow Rate

F Adding Uncertainty Measures

In this section we show that our baseline results are robust to adding the World Uncertainty index or Financial Uncertainty to the VAR.

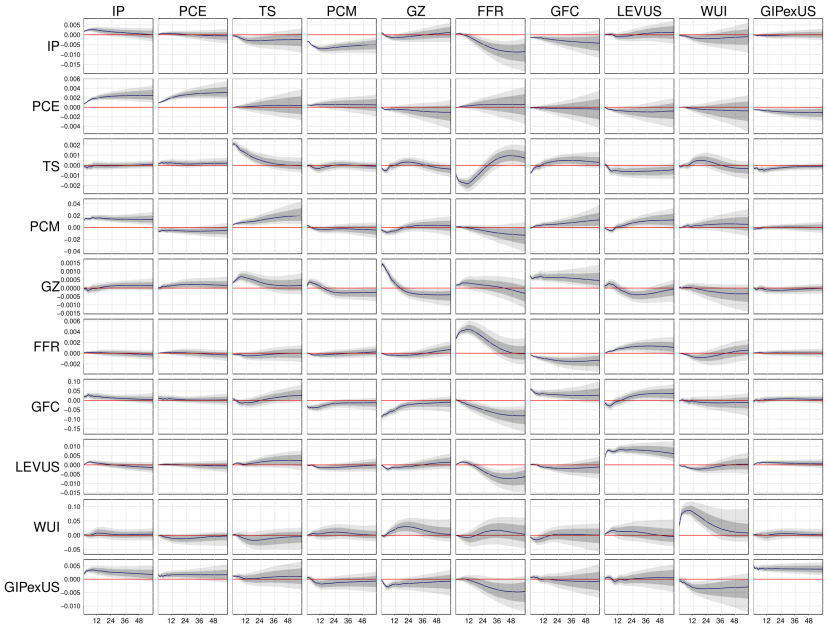


Figure A21: Impulse Responses: WUI

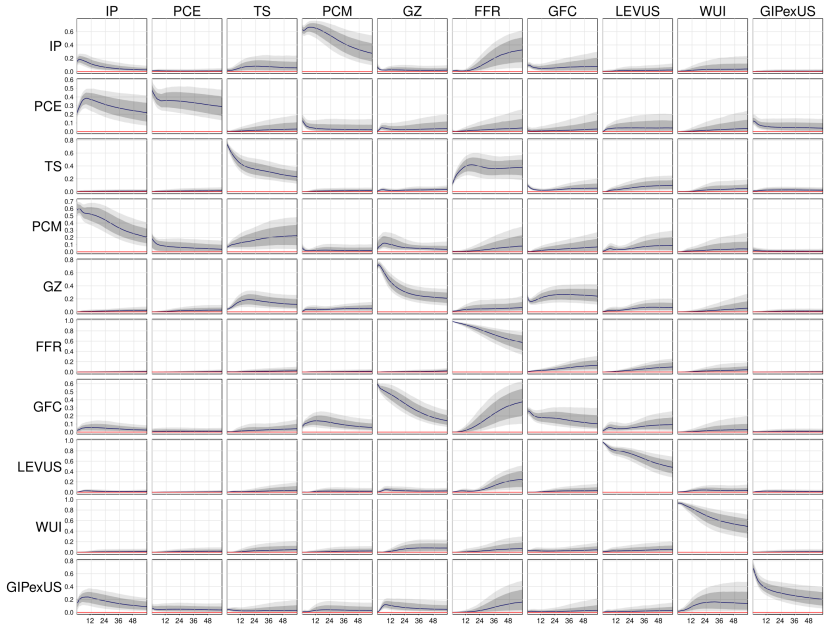


Figure A22: Variance Decompositions: WUI

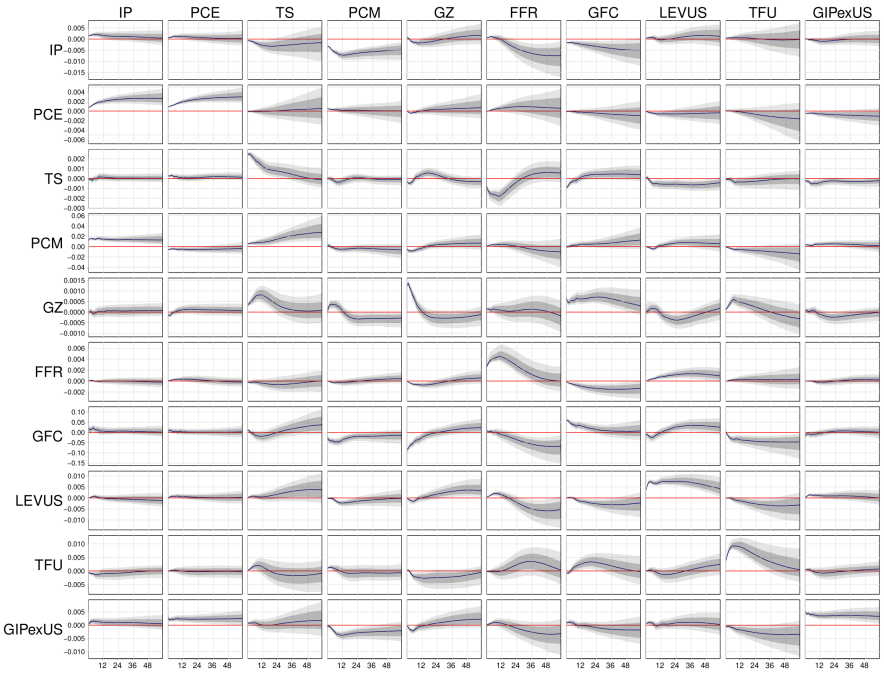


Figure A23: Impulse Responses: TFU

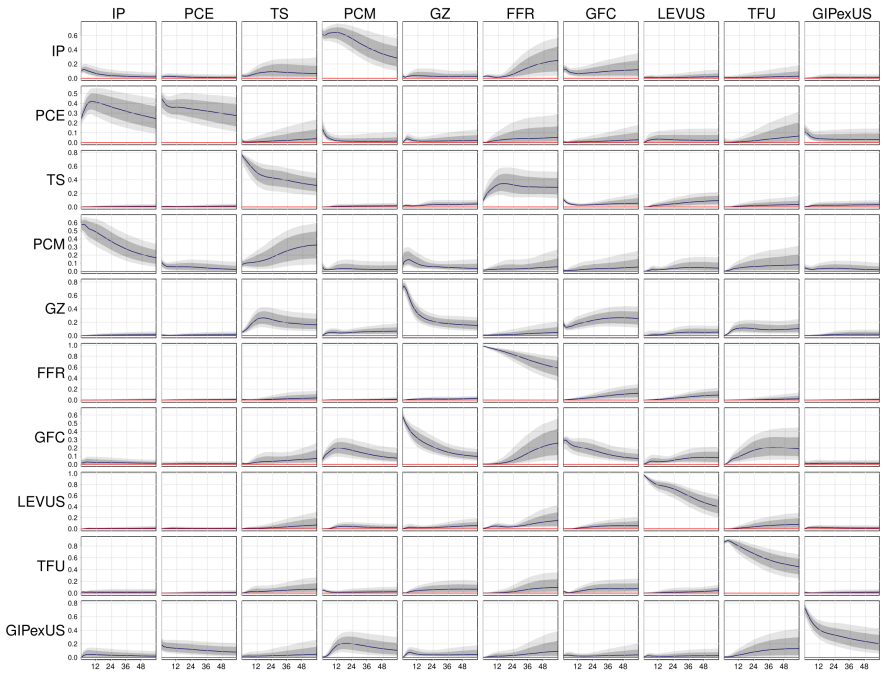


Figure A24: Variance Decompositions: TFU

G Credit Spread vs. Credit Aggregates

Our exploration of the role of the GZ spread in driving the global financial cycle highlights the importance of credit and leads to the natural question concerning the interaction between credit spreads and credit aggregates. We investigate this by examining impulse responses involving credit aggregate variables. Figure A25 show the impulse responses of the model in which we take a more detailed look at US domestic credit. As seen in the figures, domestic credit expansions boost economic activity and improve financial conditions. There's an immediate boom in the global asset price factor and increase in bank leverage following a US credit expansion. Importantly, the monetary contraction following credit supply shocks echoes the key finding of Brunnermeier et al. (2021) in that the long run decline of economic growth in response to credit expansion is spuriously correlated with the endogenous reaction of monetary authorities rather than a result of "bad credit" (see Mian et al. (2017)). Figure A26 presents the FEVDs of the model. We find similar findings as the baseline results, The GZ index accounts for most FEVs of GFC, while the US domestic credit does not seem to account for much FEVDs of GFC.

We also investigate two alternative measures of credit aggregates – the household credit (HHC) and business credit (BC) used by BPSS. This restricts our analysis to the sample period ending at May 2016, so we stick to the same regime choices as in the main text, effectively dropping the sixth regime from the estimation. As can be seen in Figure A27, the impulse responses of HHC and BC approaches that of the domestic credit measures above, and are as expected by theory both in direction and magnitude. However, the large effect of credit price is not dominated by that of the credit aggregates. In effect, the fraction of global asset price fluctuations due to credit aggregates is negligible, and credit spread shocks explain a large fraction of fluctuations in credit aggregates (after a spike in GZ spread, both the household credit and business credit drop by a large amount). Also consistent with BPSS, we document the endogenous response of credit volume in response to US monetary policy, but credit amounts themselves plays no significant role in the global financial cycle.

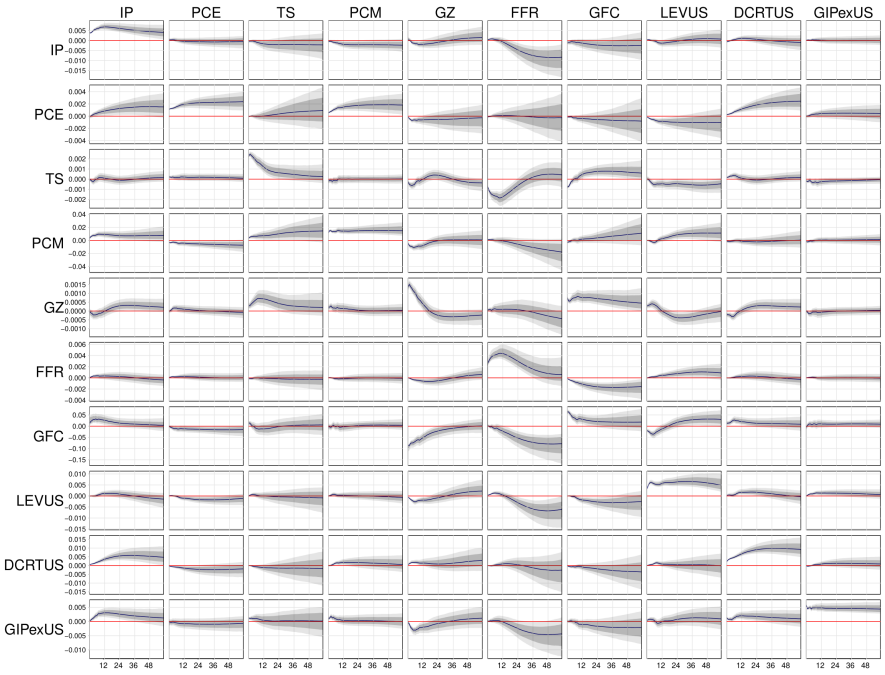


Figure A25: Impulse Responses: US Credit Aggregates

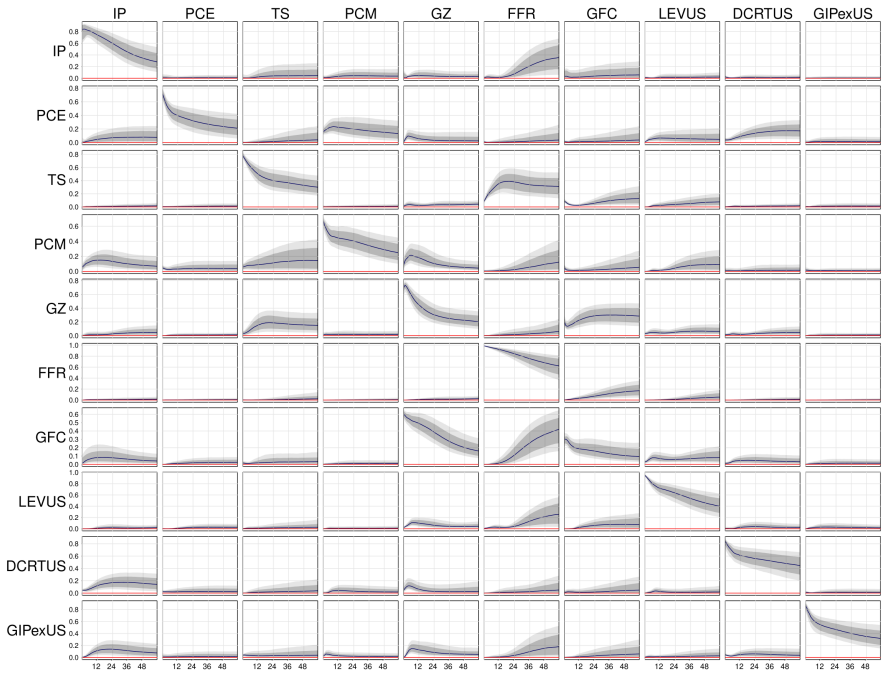


Figure A26: Variance Decompositions: US Credit Aggregates

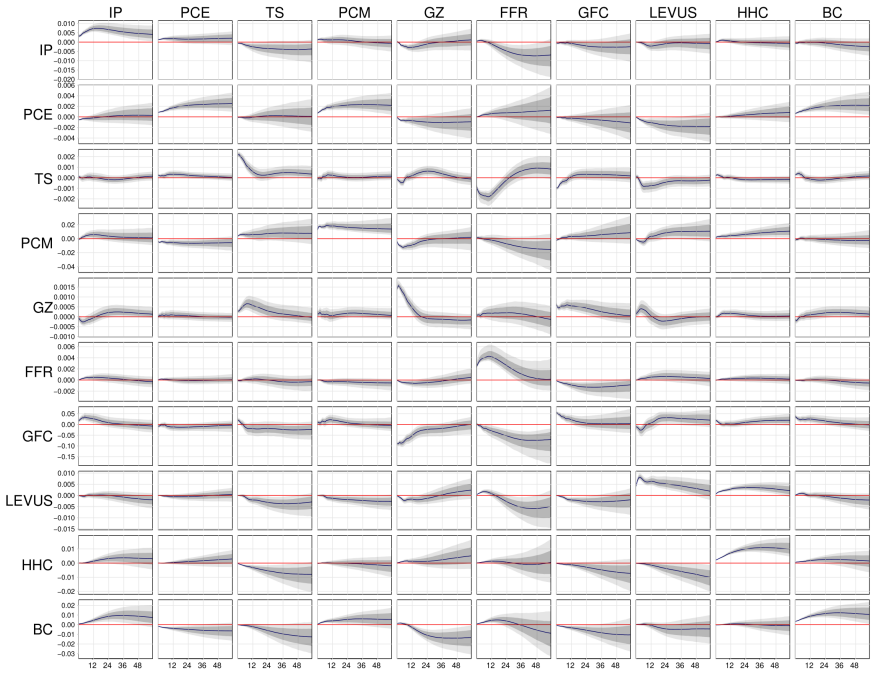


Figure A27: Impulse Responses: HHC and BC

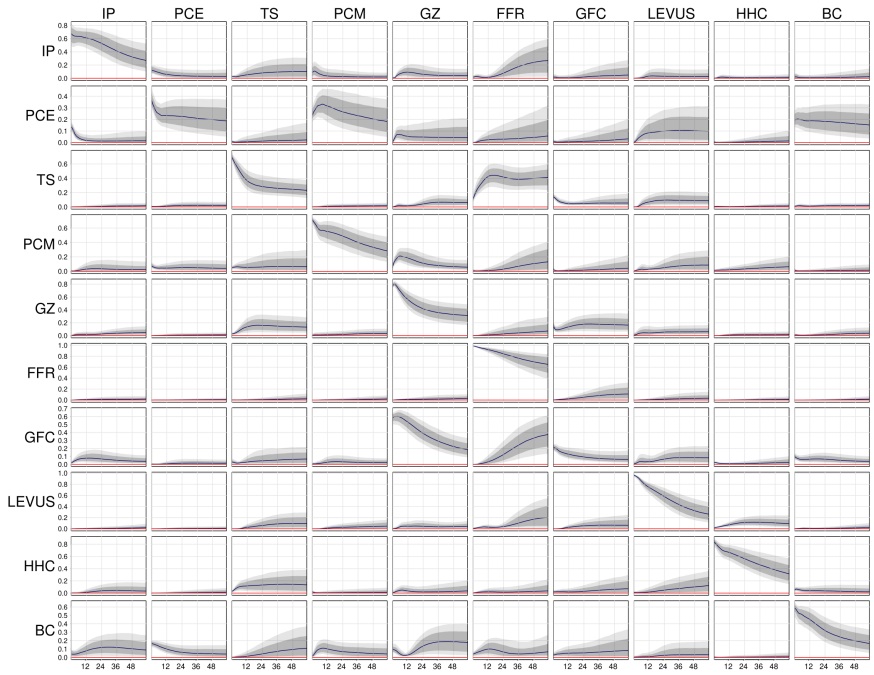


Figure A28: Variance Decompositions: HHC and BC

H Other Robustness Checks: Risk Aversion, Effective Exchange Rate, Global Capital Inflows, Global Domestic Credit, Excluding GZ Spread

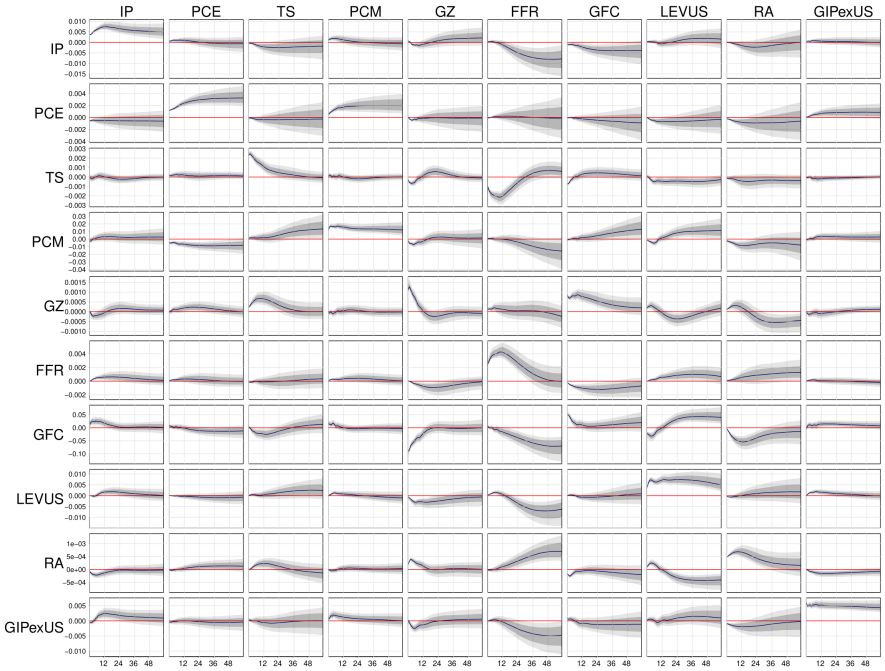


Figure A29: Impulse Responses: Risk Aversion

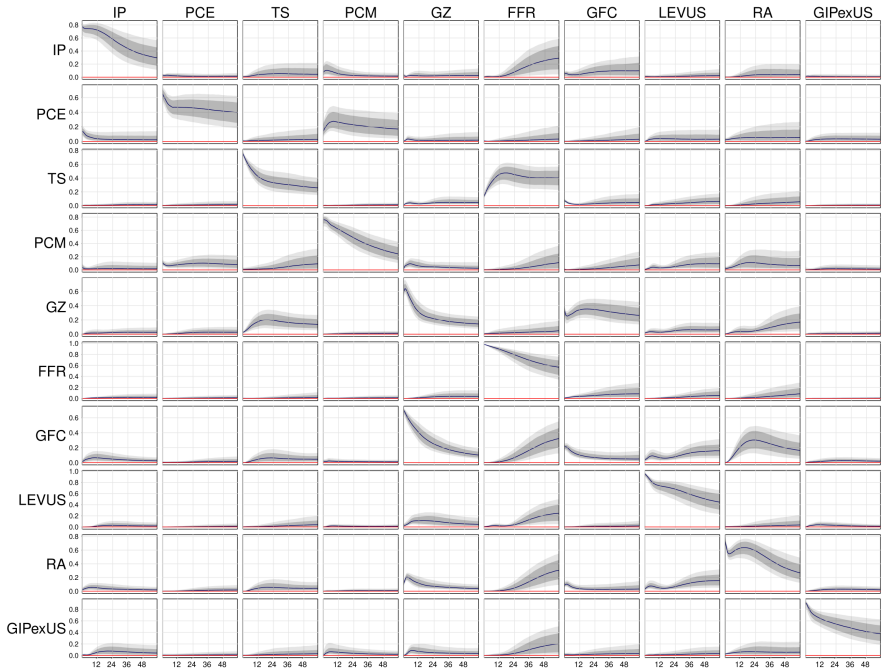


Figure A30: Variance Decompositions: Risk Aversion

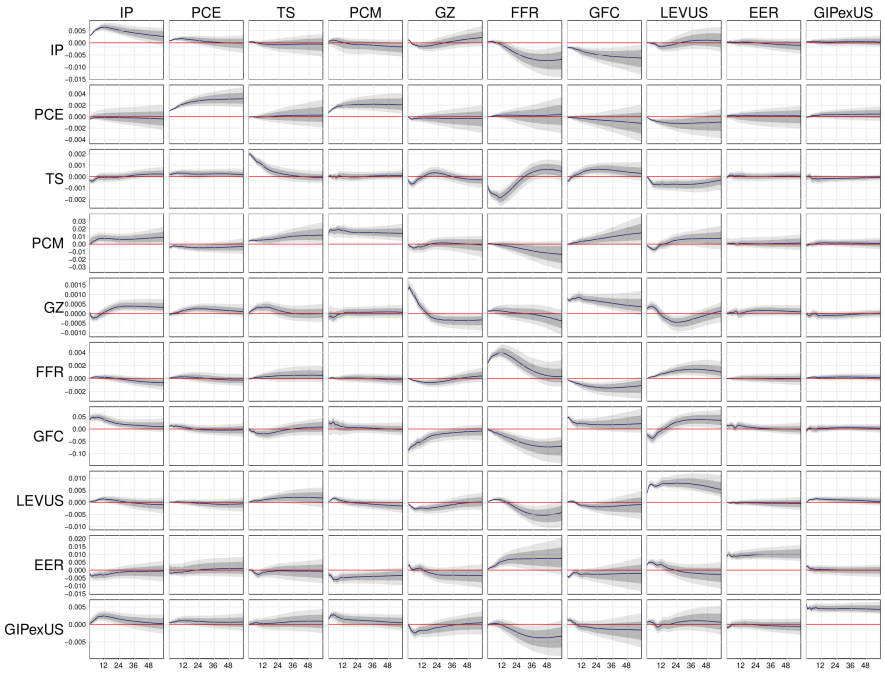


Figure A31: Impulse Responses: Effective Exchange Rate

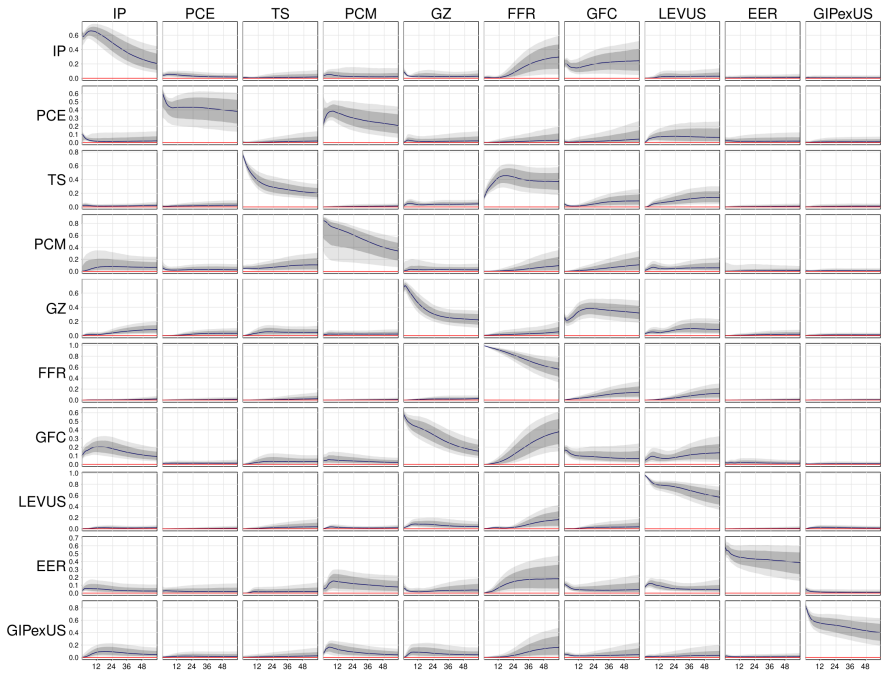


Figure A32: Variance Decompositions: Effective Exchange Rate

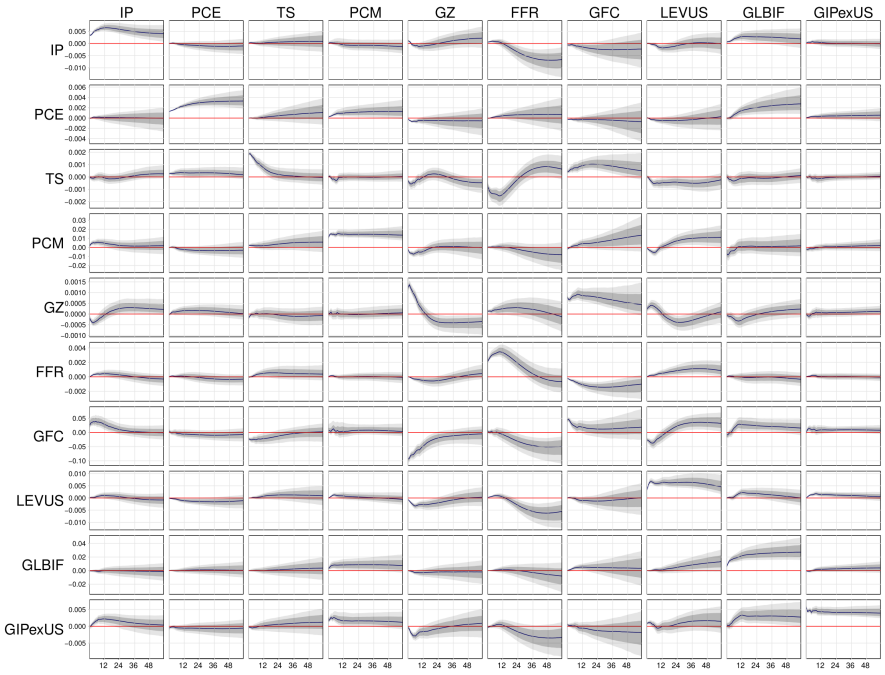


Figure A33: Impulse Responses: Global Capital Inflow

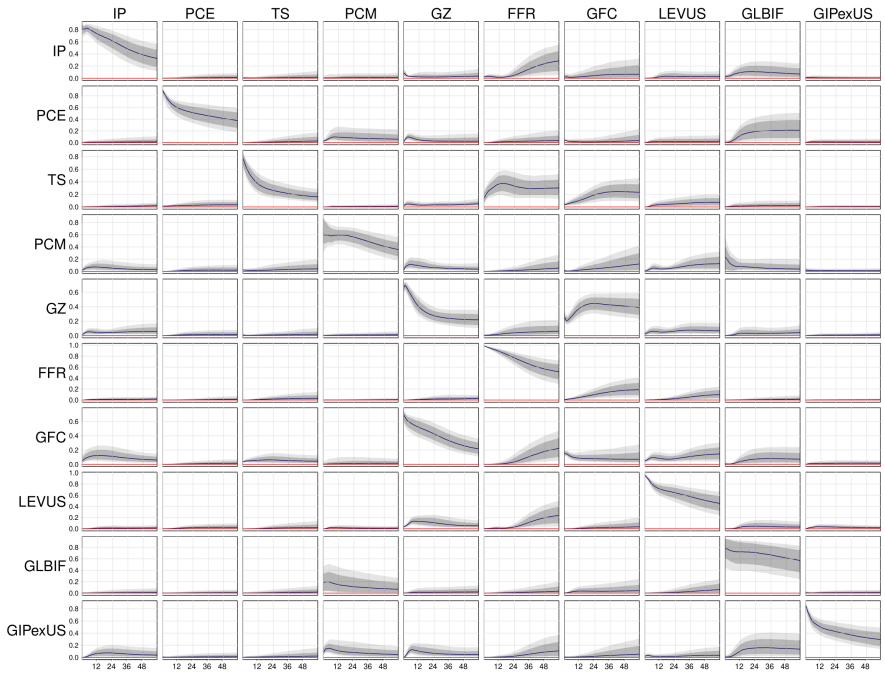


Figure A34: Variance Decompositions: Global Capital Inflow

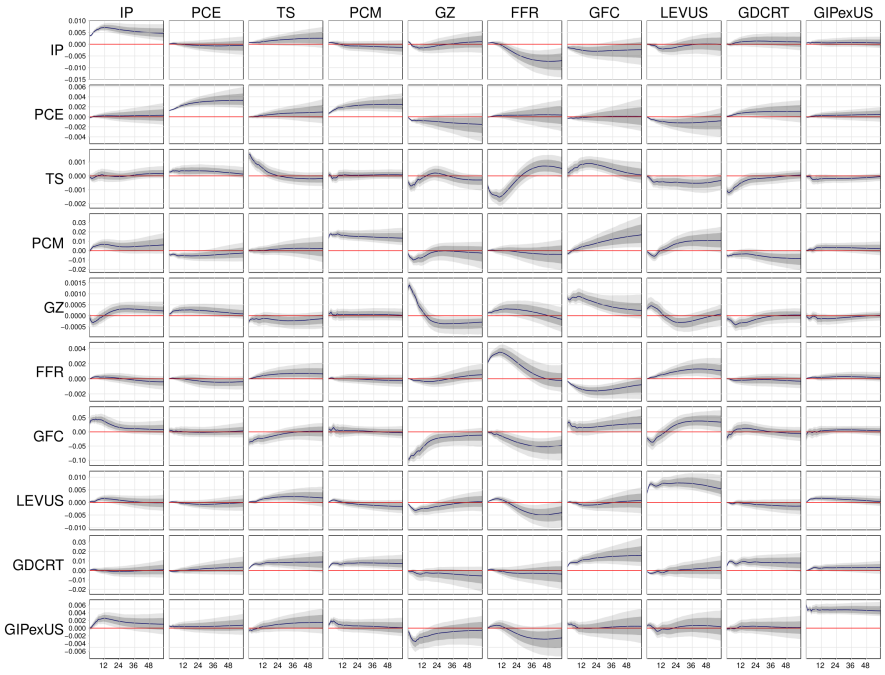


Figure A35: Impulse Responses: Global Domestic Credit

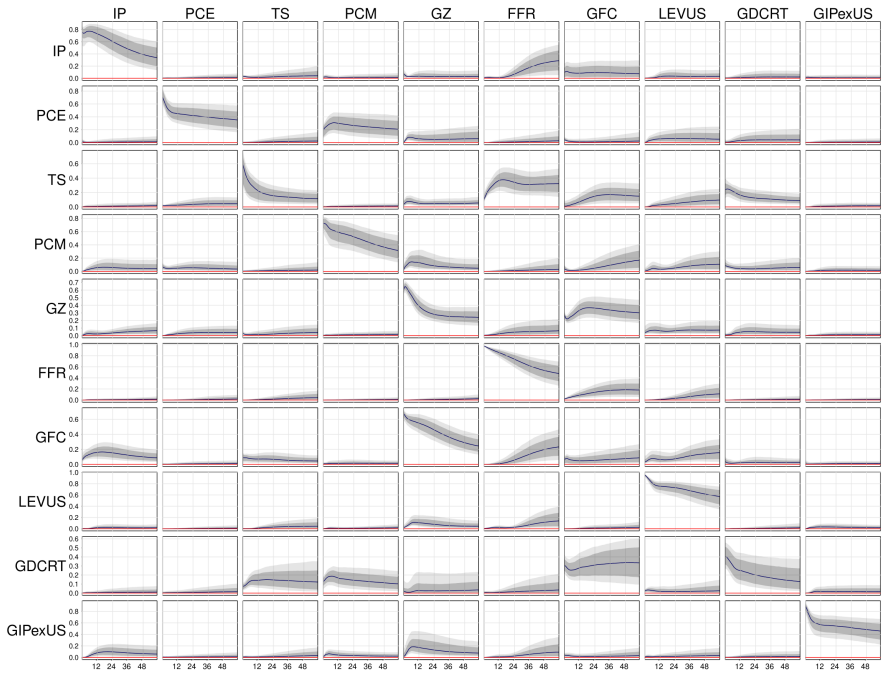


Figure A36: Variance Decompositions: Global Domestic Credit

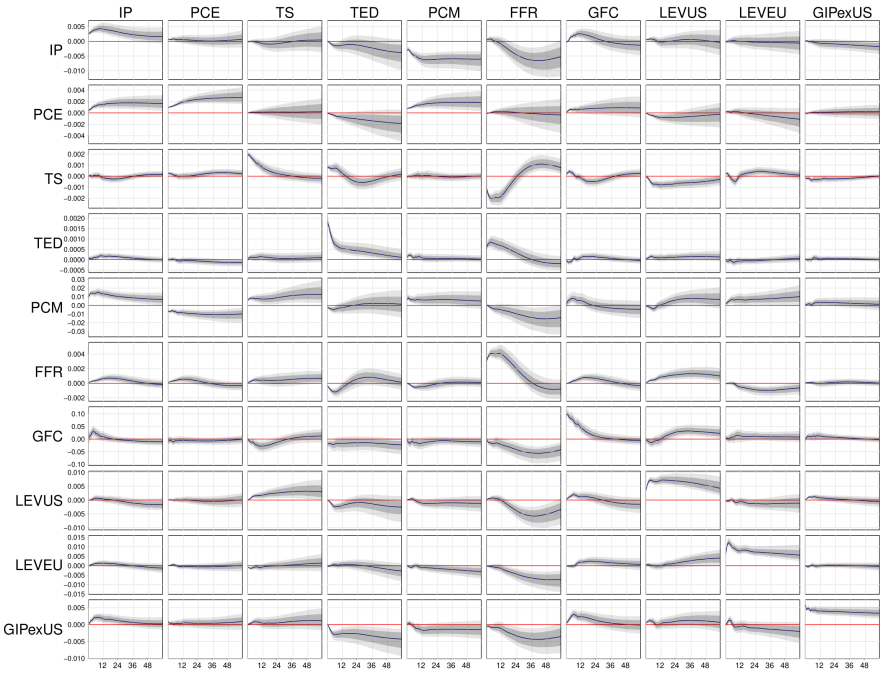


Figure A37: Impulse Responses: GZ Index Excluded

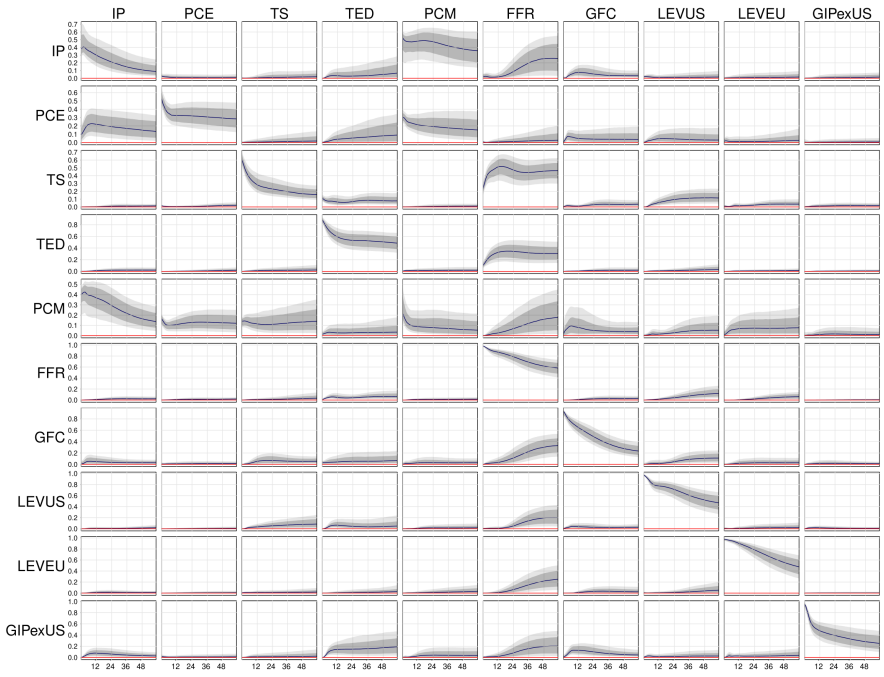


Figure A38: Variance Decompositions: GZ Index Excluded