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 predominant driver is not U.S. monetary policy, but rather shocks to (i) U.S. corporate bond spreads, in particular its excess bond premium component, (ii) leverage of U.S. banks, and (iii) the U.S. term premium. In addition, the relationship between spreads and the global financial cycle factor features a robust feedback loop that produces amplification effects. When U.S. corporate bond spreads widen, it triggers broad declines in global asset prices. This global financial downturn then feeds back into the U.S. via a further tightening of spreads. Our findings suggest that the hegemony of the U.S. in global financial systems may be rooted in the centrality of its financial intermediaries, and the dollar, rather than Fed monetary policy *per se*.

Keywords: Global Financial Cycle; Monetary Policy; Financial Shocks.

JEL codes: E44, E52, G14

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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 (2022)). Emerging-market economies in particular are subject to large gross capital inflows and outflows as market volatility and risk premia 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 (GFC) 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 quantifying relative contributions of various 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.

Importantly, we include in the VAR the Gilchrist & Zakrajšek (2012) (GZ) corporate bond credit spread index. We identify shocks to this spread — following Brunnermeier et al. (2021) — that are orthogonal to shocks to U.S. monetary policy, leverage of financial intermediaries, interest rate spreads, credit supply, and the macroeconomy. We also include in the VAR indicators of U.S. monetary policy, and again following Brunnermeier et al. (2021) identify U.S. monetary policy shocks. In effect, we are taking from Brunnermeier et al. (2021) the identified shocks to the GZ spread and U.S. monetary policy and estimating impulse responses/variance decompositions in a VAR that features the variables emphasized in GFC papers such as Miranda-Agrippino & Rey (2020b).

We derive three main results. First, the predominant drivers of the global financial cycle are shocks to (i) Gilchrist & Zakrajšek (2012) U.S. corporate bond spreads (GZ), in particular, its excess bond premium (EBP) component, (ii) leverage of U.S. banks, and (iii) the U.S. term premium.[1] A widening of U.S. corporate bonds spreads has large and immediate effects in lowering the GFC factor of Miranda-Agrippino & Rey (2020b) and raising the U.S. term premium. GZ shocks also significantly lower output in the U.S. and abroad: that is, the contractionary effect of GZ shocks Gilchrist & Zakrajšek (2012) find in the U.S. extends globally. Innovations to U.S. corporate bond spreads account for more than 20% of the volatility of the Miranda-Agrippino & Rey (2020b) at medium horizons. In addition, identified shocks to U.S. banking sector leverage and term premium 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 over the medium term, leads to reductions in global risk aversion, and prompts a non-trivial Fed tightening. This supports the emphasis placed on financial intermediary leverage in the theoretical literature. A widening of U.S. term spreads lowers the global financial cycle factor to a degree that is nearly as persistent as GZ shocks. Together, these shocks account for the bulk of the forecast error variance of the GFC factor that is not explained by the "own shock".

Second, the relationship between U.S. corporate bond spreads, the term premium, and the global financial cycle factor features a robust feedback loop that produces amplification effects. When U.S. corporate bond spreads widen, it triggers broad declines in global asset prices. This global financial downturn then feeds back into the U.S., further widening corporate bond spreads.

Third, tightening Fed monetary policy shocks have significant negative effects on the GFC

[1] Gilchrist & Zakrajšek (2012) 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. Although we primarily use the GZ spread, we find that replacing it with the EBP index yields similar conclusions. BPSS (2021) also use the GZ corporate bond spread series—rather than EBP—in their VAR.

factor, leverage of banks, U.S. term spreads, and U.S. output. Compared to shocks to U.S. corporate bond spreads, banking leverage, and the term premium, U.S. monetary policy shocks play a smaller role in explaining the global financial cycle, either directly or in an amplification sense. U.S. monetary policy shocks account for less than (typically much less than) 10% of the forecast error variance of the global factor across horizons, VAR specifications, and indicators of U.S. monetary policy.

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. A recent paper by Akinci & Queralto (2024) highlights the significance of UIP deviations underlying large cross-border spillovers of U.S. monetary policy shocks. A failure of UIP—stemming from financial imperfections that limit the ability of emerging market borrowers to obtain foreign-currency denominated financing—can give rise to an adverse feedback between financial health and external conditions, amplifying the effects of U.S. monetary policy shocks on emerging markets.

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 global financial cycle 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. Dées & Galesi (2021) show that network effects —a network of interactions across countries—play a quantitatively important role in amplifying the effects of U.S. monetary policy surprises on international equity prices, capital flows, and global growth. In their exhaustive review of the literature, Miranda-Agrippino & Rey (2022) 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 not only uses the econometric identification procedure of Brunnermeier et al. (2021), but shares the spirit of their application. These authors examine feedback between U.S. credit shocks and U.S. output using an 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." We also rank the contribution of U.S. monetary policy shocks relative to others, now in a global context. Another important finding of Brunnermeier et al. (2021) 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.

2 Econometric Framework

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 heteroscedasticity lets us do this with more plausible assumptions than 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 plausibly uncorrelated with any other source of economic disturbances.[2]

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 $\mathcal{T} \coloneqq \{1, \dots, T\}$ 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

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

where $\gamma_{i,m(t)}$ is the ith diagonal entry of $\Gamma_m(t)$.[3] 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.[4]

Finally, we follow Brunnermeier et al. (2021) to allow for possible rare events to provide more

[2] 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. (2021) and Arias et al. (2018). See Brunnermeier et al. (2021) and Wolf (2020), Bertsche & Braun (2022) for further discussion of the relative merits of different procedures and the arguments in favor of a heteroscedasticity-based approach. For a critical review, see Montiel Olea et al. (2022).

[3] 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.

[4] 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 falls on the mis-specification of the constant $C(L)$. Brunnermeier et al. (2021) provide evidence that this specification outperforms some models that allow $C(L)$ to vary.

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 $\{y_1, \dots, y_T\}$ and initial conditions $\{y_{-p-1}, \dots, y_0\}$.

3 Estimation

3.1 Data and Variable Construction

We summarize the variables included in our various VAR systems in Table 1. 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 runs through 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. This series is depicted in Figure 1. 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).[5] In addition, we use the risk appetite measure of Bauer, Bernanke & Milstein (2023), which is available beginning in 1988.

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

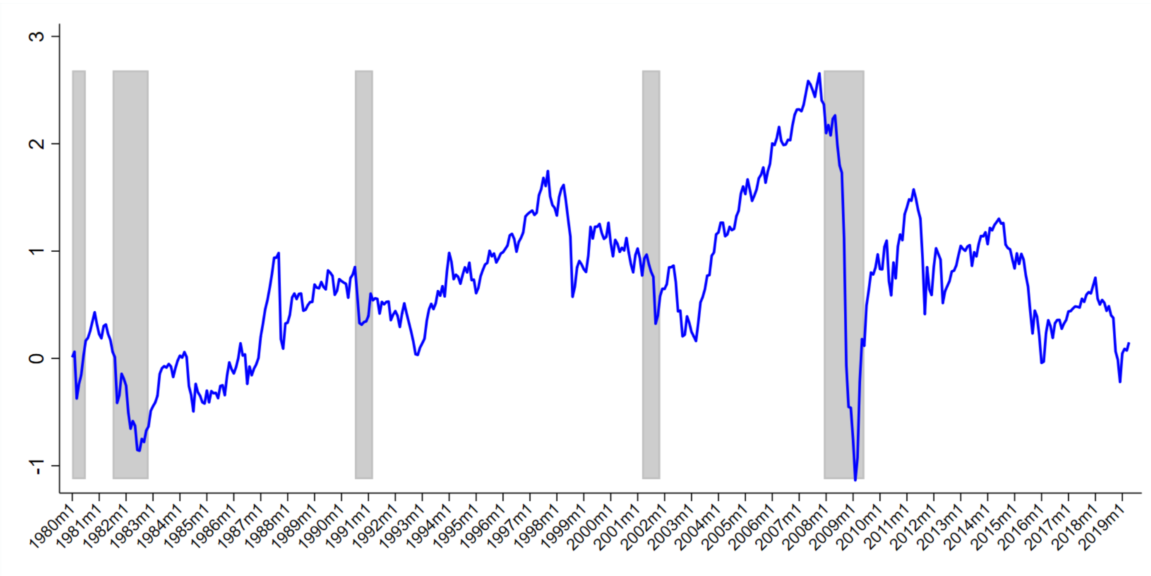


Figure 1: Global Financial Cycle Factor

We also include the effective Federal Funds interest rate as a proxy for U.S. monetary policy. This follows Brunnermeier et al. (2021). 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)) and the forward guidance shock of Swanson (2021) in place of FFR. Furthermore, we examine robustness to using U.S. monetary policy shock series identified through external instruments, and the effects of adding the ECB Deposit Facility Rate.

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. The U.S. corporate bond spread and (GZ) excess bond premium (EBP) measure are from Gilchrist & Zakrajšek (2012), Gilchrist et al. (2021). These series are also used by Brunnermeier et al. (2021) and Miranda-Agrippino & Rey (2020b).[6]

For the country-level measure of banking sector leverage we follow Forbes (2012) and calculate

[6] As listed in Table 3, our 10-variable baseline VAR model contains six of the ten series used by Brunnermeier et al. (2021). We don't use 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, 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.

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 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.

Table 1: Data Series Used

Variables	Description
IP	US industrial production from FRED (code: INDPRO)
GFC	Global factor estimated by Miranda-Agrippino et al. (2020)
Risk aversion	Global risk aversion decomposed from GFC
Risk appetite	Risk appetite measure of Bauer et al. (2023)
FFR	Federal Funds Effective Rate from FRED (code: DFF)
WX	Wu-Xia Index as in Wu & Xia (2016)
FG	Forward Guidance as in Swanson (2021)
BRW	"Unified" shock in Bu et al. (2021)
NS	"Policy news" shock of Nakamura & Steinsson (2018), updated by Acosta (2022)
ECBD	Deposit Facility Rate for Euro Area
PCE	Personal consumption expenditures price index from FRED (code: PCEPI)
PCM	CRB/BLS spot (commodity) price index from Bloomberg
EER	U.S. 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)
GIPexUS	The world industrial production excluding the US calculated by authors
GLBIF	Global inflows all sectors from BIS
DCRTUS	US Domestic Credit, extended from Miranda-Agrippino & Rey (2020b)
GDCRT	Global Domestic Credit, constructed as Gourinchas & Obstfeld (2012)
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
WUI	World Uncertainty Index from Ahir et al. (2022)
FU	Financial Uncertainty from Jurado et al. (2015)

Following Gourinchas & Obstfeld (2012), we construct global domestic credit (GDCRT) as the difference between domestic claims to all sectors and net claims to the central government, reported by financial institutions excluding the central bank.[7] 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. We also use U.S. national domestic credit (DCRTUS), extending the same series in Miranda-Agrippino & Rey (2020b) to April 2019. These series are used in robustness checks designed to illuminate transmission channels. Furthermore, we include in robustness checks global capital inflows (GLBIF)—taken from the BIS—as in Miranda-

[7]Specifically, we use the Other Depository Corporation Survey in 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.

Agrippino & Rey (2020a), the log of the MSCI global index (MSCI) to capture global stock market dynamics, and global industrial production index (GIPexUS) calculated as the average of industrial production for 78 countries, excluding the U.S., available in the IMF International Financial Statistics database. Finally, we consider various uncertainty measures, including the World Uncertainty Index (WUI) of Ahir et al. (2022) and Financial Uncertainty (FU) of Jurado et al. (2015).

Table 2: Baseline Regime Choices

	Start	End	Description
1	Jan 1988	Dec 1989	Recovery from early 1980s recession
2	Jan 1990	Dec 2007	Great Moderation and Greenspan Federal Reserve
3	Jan 2008	Dec 2010	Great Recession
4	Jan 2011	Dec 2015	Zero Lower Bound, Recovery from Great Recession
5	Jan 2016	Apr 2019	Monetary policy normalization

3.2 Regime Choices

In our baseline analysis, with data spanning January 1988 to April 2019, we split the data into five regimes summarized in Table 2. The first captures the recovery from the early 1980s recession, and also includes some distinct dynamics due to the S&L crisis. The second regime is the "Great Moderation", characterized by less erratic monetary policy and more predictable macro aggregates. These two regimes, 1988-2007, are sometimes jointly thought of as the "Great Moderation", which is featured by less erratic monetary policy and more predictable macro aggregates. In view of the fact that the volatility caused by S&L crisis might have made the initial period somewhat different in macro dynamics, we distinguish it from the second and consider it independently. The third regime is the financial crisis, during which many macro variables, and especially financial variables, became significantly more volatile. The fourth 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 1.2, examining "global regimes" that include the 1997 Asian financial crisis and the European debt crisis. We show that results are highly robust.

Table 3: VAR Variables

Variable	Source	VAR Models				
		(1)	(2)	(3)	(4)	(5)
		Baseline	Alternative Regimes	Robustness	BPSS	MAR
IP	FRED	✓	✓	✓	✓	✓
PCE	FRED	✓	✓	✓	✓	✓
TS	FRED	✓	✓	✓	✓	
PCM	Bloomberg	✓	✓	✓	✓	
GZ	GZ	✓	✓	✓	✓	✓
EBP	GZ			$\checkmark^a$		
FFR	FRED	✓	✓	✓	✓	
1-yr T rate	FRED					✓
WX	Wu-Xia			$\checkmark^b$		
FG	Swanson			$\checkmark^b$		
BRW	Bu-Rogers-Wu			$\checkmark^b$		
NS	Nakamura-Steinsson			$\checkmark^b$		
ECBD	ECB			✓		
LEVUS	IFS*	✓	✓	✓		✓
LEVEU	IFS*	✓	✓			✓
GFC	MARb	✓	✓	✓		✓
GIPexUS	OC and BH	✓	✓	✓		✓
TED	FRED				✓	
M1	FRED				✓	
Risk appetite	BBM			$\checkmark^c$		
EER	BIS			$\checkmark^*$		
Glob inflows	BIS			$\checkmark^*$		✓
DCRTUS	IFS*			$\checkmark^*$		
GDCRT	OC			$\checkmark^*$		✓
MSCI	MSCI			$\checkmark^*$		
Risk aversion	OC and BEX			$\checkmark^*$		✓
Uncertainty	WUI, FU			$\checkmark^*$		

Notes: Variables included in Brunnermeier et al. (2021), in the baseline global model of Miranda-Agrippino & Rey (2020b) (Model 2), and in our various global models. Miranda-Agrippino & Rey (2020b) use for the Leverage series a different source of data than we do and furthermore break down U.S. leverage into banks and broker-dealers and EU leverage into "banks" and "global banks". They use the 1-year Treasury bill rate as the monetary policy indicator. We 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 $\checkmark^a$ denotes the robustness check where we replace the GZ spread with EBP; $\checkmark^b$ denotes the robustness check where we replace FFR with either the Wu & Xia (2016) shadow interest rate, the Swanson (2021) forward guidance shock (available beginning in 1991), the Bu et al. (2021) "unified" shock, or the Nakamura & Steinsson (2018) policy news shock; $\checkmark^c$ denotes that we replace GZ with risk appetite measure of Bauer et al. (2023); $\checkmark^*$ 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. (2021). 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.

4 The Structural Shocks

This section begins with an overview of the impulse responses. As in Brunnermeier et al. (2021), our estimation simply separates the shocks without giving them economic interpretations. We therefore provide that interpretation below. We describe in Table 3 the variables included in our baseline global VAR (column 1), our various robustness models (columns 2-3), and in Brunnermeier et al. (2021) and Miranda-Agrippino & Rey (2020b) for comparison purposes (columns 4 and 5). We estimate the model with 10 lags at monthly frequency over the sample 1988:1 - 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).

We report impulse responses from our baseline HB-SVAR in Figures 2 through 6. For improved exposition, we split results according to "financial" and "real" responses. In Figure 2, we show the impulse responses of FFR, GZ, LEVUS, GFC, and TS, while in Figure 3 we report responses to U.S. and global output, prices, and LevEU.[8] We organize description of the results by shock, highlighting shocks to U.S. monetary policy, GZ spreads, Leverage, and GFC.

4.1 U.S. Monetary Policy Shocks

Column (1) of Figure 2 presents the impulse responses of financial variables to the U.S. monetary policy shock in the baseline SVAR. A tightening monetary policy shock raises the Federal Funds interest rate and leads to a marginally significant increase in the GZ corporate bond spread and a significant deleveraging of U.S. banks. The shock also leads to a drop in the Miranda-Agrippino & Rey (2020a) global price factor on impact and over medium horizons, as well as a significant drop in the term premium for nearly two years. In terms of real variable responses (Figure 3, column (1)), a tightening U.S. monetary policy leads to a significant decline in industrial production and commodity price indexes, a slight deleveraging of EU banks, and an eventual drop in global industrial production.[9]

[8]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).

[9]We find that U.S. monetary policy shocks become more important at longer horizons, echoing results in Brunnermeier et al. (2021) and Jordà et al. (2020), who find large and persistent effects of monetary policy shocks in a closed-economy VAR model for the U.S. and in a cross-country panel, respectively. Even in the GFC literature, as discussed below, some significance of U.S. monetary policy is found at 7–10 quarters or later.

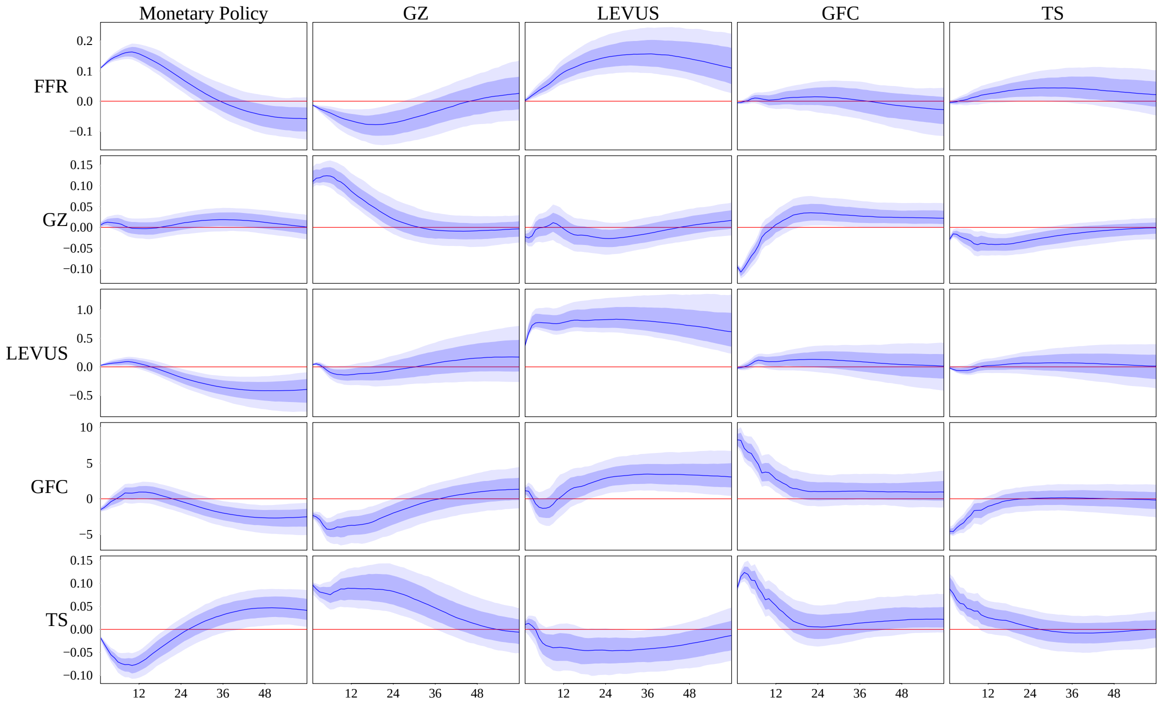


Figure 2: HB-SVAR Impulse Responses: Global VARs, Baseline (1/4)

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

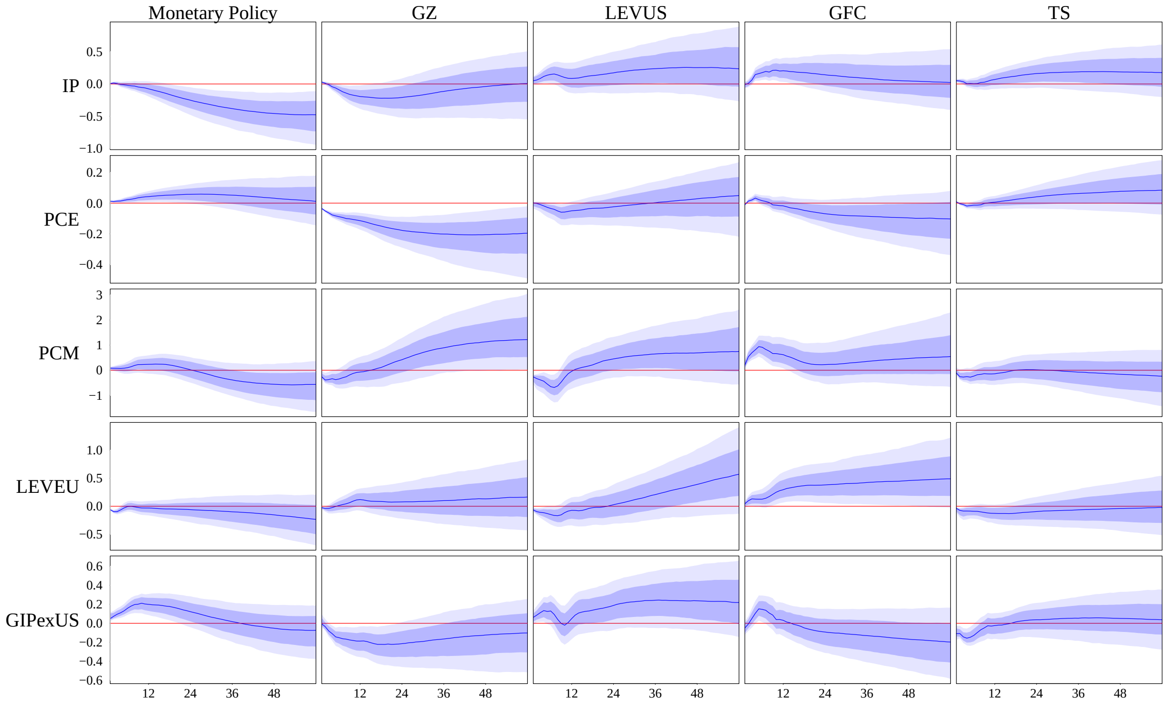


Figure 3: HB-SVAR Impulse Responses: Global VARs, Baseline (2/4)

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

As evidence of the plausibility of the U.S. monetary policy shock, we compare the impulse responses in our model to those of Brunnermeier et al. (2021) for the variables the two papers share in common. As shown in the first column of Figure 4, the impulse responses to the U.S. monetary policy shock in our model are quite similar to those of BPSS. Both lead to a small rise in GZ corporate bond spreads while their (larger) monetary policy tightening shock produces a (slightly larger) decline in IP and prices, as well as a larger decline in the term premium, in comparison.

4.2 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 (2) of Figure 2 and Figure 3, we display the responses to identified GZ credit spreads shocks. A positive GZ shock leads to a decline in both U.S. and global industrial production, a short run drop in PCE and PCM, and a steepening in the term structure. In addition, monetary policy loosens in response. Importantly for our purposes, the GZ shock leads to a significant decline in the global financial cycle factor and slight deleveraging of the U.S. banking sector. Note from column (2) of Figure 4 that the impulse responses to the GZ shock in our model are once again highly similar to responses to the GZ shock in Brunnermeier et al. (2021), with the exception of the term premium. The responses to GZ shocks in our model 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 a positive GZ shock cannot be attributed to an endogenous tightening of U.S. monetary policy because policy loosens.

4.3 Shocks to Leverage and Term Spread

Theoretical accounts of the global financial cycle emphasize the importance of financial intermediaries' leverage positions, as discussed above. Column (3) of Figure 2 indicates that a positive shock to U.S. banking sector leverage has small expansionary effects. It leads to an increase in the Miranda-Agrippino & Rey (2020b) global price factor and a small decrease in GZ over the medium term, in spite of a non-trivial tightening of U.S. monetary policy. This is consistent with the theory that leverage is procyclical and amplification effects can add to systematic risk over time. Shocks to U.S. banking sector leverage have small but positive effects on real variables, as seen in Figure 3.

We also find that a shock that widens term spreads leads to a significant decline in global asset prices. The downturn in the global financial cycle is accompanied by monetary policy tightening in the medium term and GZ spreads narrowing in the near term, both of which are small in magnitude. The expectation of tighter monetary policy can depress global asset prices via the discount rate effect. Portfolio rebalancing away from equities in response to term spread increases could additionally contribute to declines in global asset prices, while slightly narrowing corporate bond spreads.

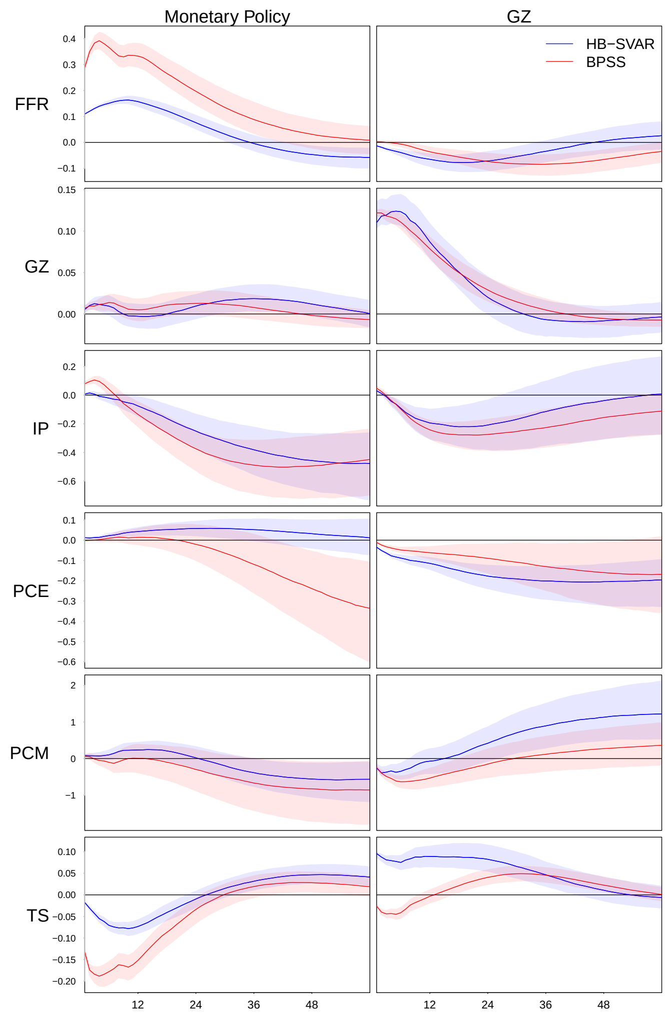


Figure 4: Comparison with BPSS: Responses to Monetary Policy Shocks and GZ Shocks

Note: Impulse responses of the variables that are common to our VAR and that of Brunnermeier et al. (2021). The latter are estimated over January 1973-June 2015. t-distributed errors over 60 months, with 68 percent posterior uncertainty regions. Scaled to an “average” period with unit scale.

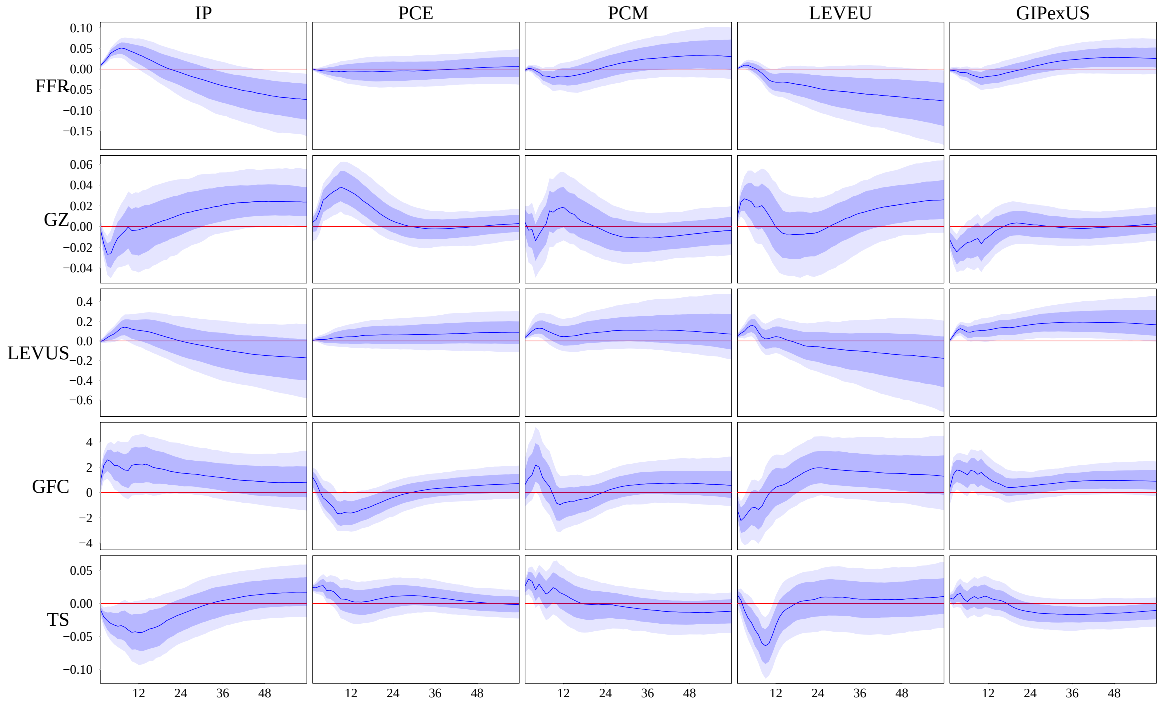


Figure 5: HB-SVAR Impulse Responses: Global VARs, Baseline (3/4)

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

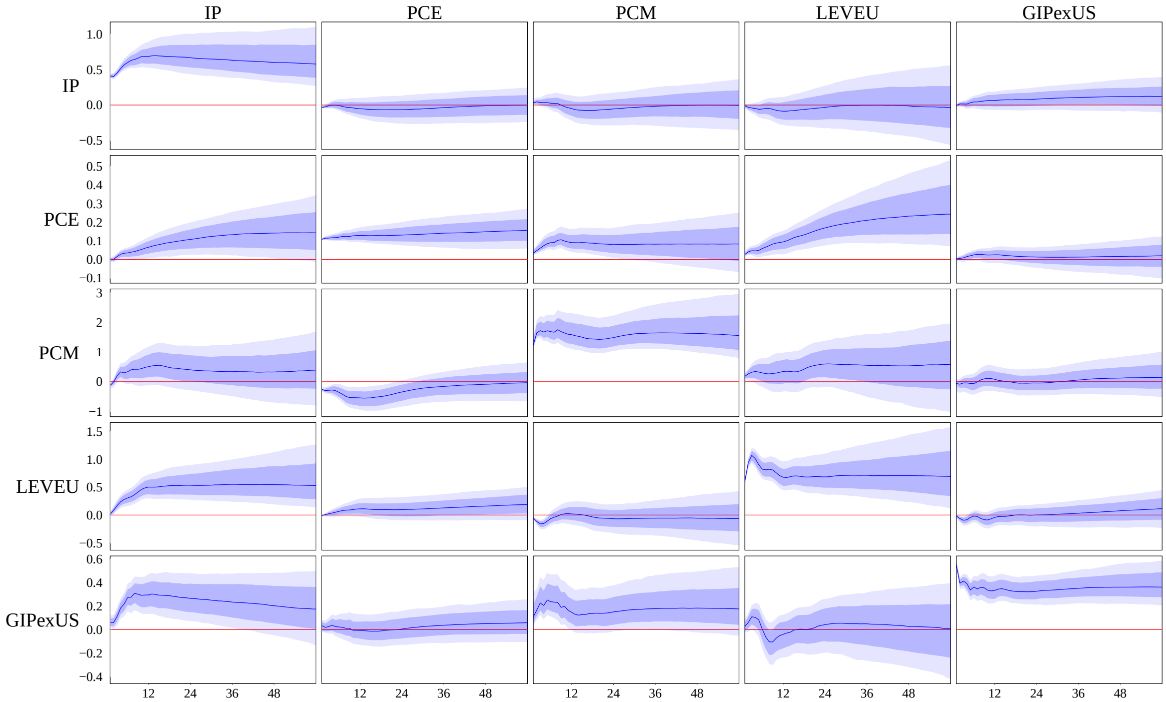


Figure 6: HB-SVAR Impulse Responses: Global VARs, Baseline (4/4)

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

4.4 Structural Shock Volatility

A key to our identification is the assumption that the variances of each equation in the baseline t-errors model (i.e., γ_{im} above) 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 lead to ill-determined results.[10] With this in mind, Table 4 reports the estimated variances of each equation in the baseline model, by regime sub-period. There is clearly strong time-variation in the shock variances. The variances of financial shocks spike during the financial crisis (Regime 3). The monetary policy shock, as expected, shows elevated variances earlier in the sample and almost zero variance during the zero lower bound period. The 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 global financial crisis. Industrial production and commodity price shocks are most volatile during the Great Recession, but 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 1988-Dec 1989	Jan 1990-Dec 2007	Jan 2008-Dec 2010	Jan 2011-Dec 2015	Jan 2016-Apr 2019
IP	0.961	0.831	1.749	0.663	0.800
PCE	1.012	1.454	1.020	0.655	0.830
TS	0.739	1.680	1.565	0.527	0.479
PCM	0.356	1.007	1.974	0.785	0.906
GZ	0.401	0.574	3.394	0.251	0.381
Monetary policy	1.759	0.993	1.931	0.037	0.265
GFC	0.419	0.765	1.111	1.693	0.973
LEVUS	0.065	0.376	3.217	0.677	0.679
LEVEU	0.484	0.417	0.406	2.187	1.536
GIPexUS	0.610	1.341	0.900	0.938	1.223

Note: The estimates are posterior medians with t-distributed innovations.

We present further evidence on shock volatility in Table 5, which lists the four largest posterior median shocks for each variable. The biggest of these, for the GZ spread shocks, coincides with the market turmoil during the sub-prime mortgage crisis and the Lehman Brothers collapse. Furthermore,

[10] Though they also note, "The Achilles heel of this approach to identification, then, is not the possibility of little heteroskedasticity, but rather this possibility that the assumption of constant A(L) is incorrect." They provide evidence that their model outperforms models that allow $A(L)$ (our $C(L)$ above) to vary.

we document a dramatic deleveraging of EU 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.[11]

Table 5: Largest Residuals For Each Shock

Month	ϵ_{it}	dy_{it}	Month	ϵ_{it}	dy_{it}
IP			FFR		
2008-09-01	-10.098	-0.049	2008-02-01	-6.891	-0.009
2005-09-01	-5.278	-0.025	1992-07-01	-4.482	-0.005
1998-08-01	4.167	0.026	1991-02-01	-4.220	-0.005
2008-08-01	-3.582	-0.017	1994-11-01	4.146	0.005
PCE			GFC		
2005-09-01	5.967	0.009	2011-10-01	4.752	0.521
2001-10-01	4.502	0.003	2008-10-01	-4.575	-0.971
1990-01-01	4.443	0.005	2011-08-01	-4.569	-0.402
2006-09-01	-4.335	-0.006	2011-09-01	-3.927	-0.513
TS			LEVUS		
2009-01-01	7.666	0.006	2001-11-01	5.447	0.025
2004-04-01	4.604	0.007	2009-02-01	-5.430	-0.024
1990-09-01	4.253	0.005	2001-10-01	5.121	0.024
1990-08-01	4.243	0.005	2009-01-01	-4.729	-0.020
PCM			LEVEU		
2008-02-01	5.385	0.065	2013-04-01	-10.388	-0.079
1997-12-01	-4.281	-0.058	2013-05-01	6.227	0.047
2009-04-01	3.667	0.050	2017-01-01	3.702	0.028
1998-11-01	-3.435	-0.050	1999-01-01	-3.638	-0.030
GZ			GIPexUS		
2008-10-01	12.782	0.024	1993-01-01	13.608	0.073
2009-01-01	-7.801	-0.014	1994-04-01	4.758	0.022
2008-09-01	4.712	0.009	1993-02-01	4.447	0.022
2001-09-01	3.754	0.008	2008-12-01	-4.250	-0.028

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

5 Accounting for the Global Financial Cycle

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 8-11 we display the full set of forecast error

[11] The largest shock observations depicted here overlap closely with those reported in Table 5 of Brunnermeier et al. (2021). 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.

variances explained by each shock in the baseline HB-SVAR model and in Figure 12 we display an historical decomposition of the GFC factor itself.

5.1 Forecast Error Variance Decomposition

Before turning to the full set of results, in Figure 7 we hone in on the forecast error variance decomposition (FEVD) of the GFC factor alone. While most of the forecast error variance is accounted for by the "own shock", especially in the short run, GZ shocks and TS shocks account for significant shares at medium term horizons of up to two years. Shocks to the leverage of U.S. banks are also important at medium to long horizons. Shocks to U.S. monetary policy, U.S. output & prices, and EU banking leverage explain relatively small shares of the GFC factor.

We depict the full set of FEVDCs by blocks, by analogy to our presentation of the IRFs. Figure 8 shows the variance decompositions of the financial 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 a small but significant fraction of leverage at medium to long horizons. Turning to the real variables, we see in Figure 9 that monetary policy shocks explain a non-trivial share of output variability after horizons of around one year.

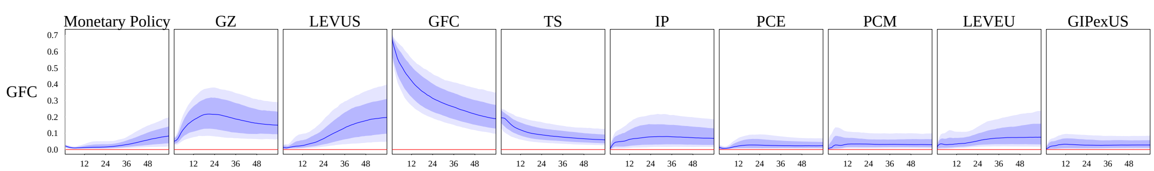


Figure 7: Variance Decomposition of the Global Financial Cycle Factor

Note: Forecast error variance decompositions for the Miranda-Agrippino & Rey (2020b) financial cycle factor in the baseline model with t-distributed errors over 60 months, with 68 percent (dark blue) and 90 percent (light blue) posterior uncertainty regions. Scaled to an "average" period with unit scale.

As noted above, our identification strategy uncovers an important role of GZ spreads in driving the global financial cycle. According to column (2) of Figure 8, GZ shocks also account for a large share of movements in the term spread. Turning to the remaining VDC results, we see that U.S. Leverage shocks account for significant fractions of FFR, TS, and output. In addition, GFC shocks account for a sizable share of the forecast error variance of GZ and TS, and a non-trivial fraction of U.S. output and prices. Shocks to the U.S. term spread (TS) are important for the GFC factor, as noted above, while U.S. output shocks explain small and imprecisely estimated amounts of all series except itself.

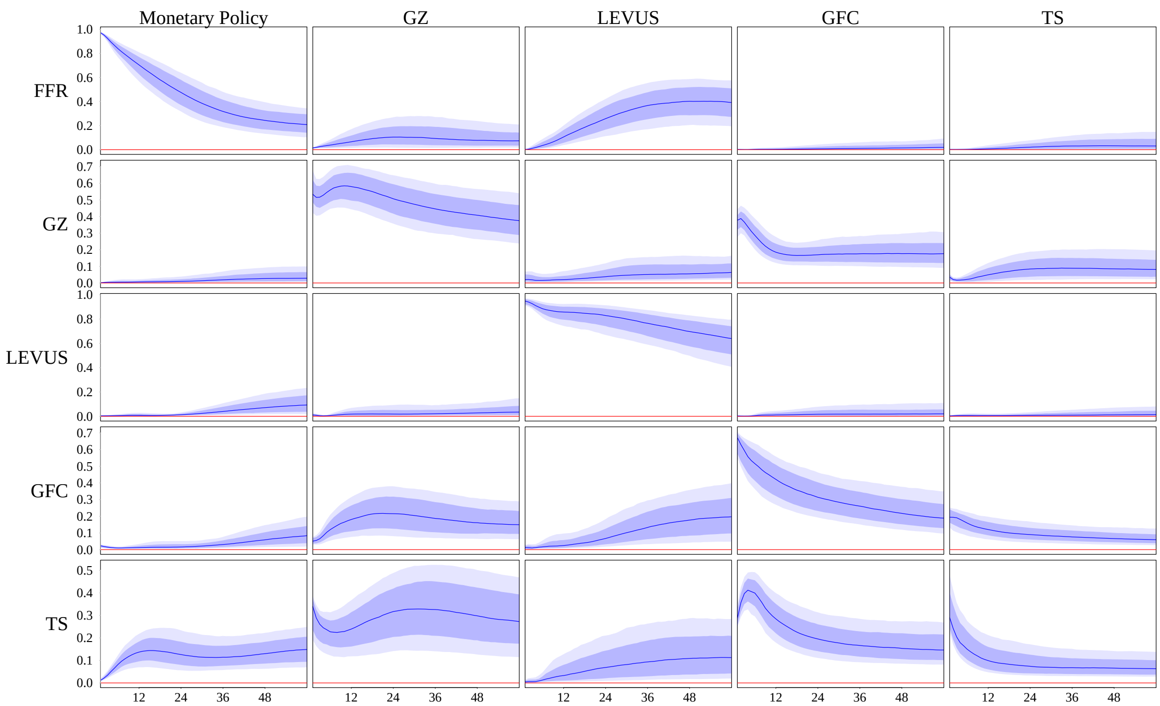


Figure 8: HB-SVAR Variance Decomposition: Global VARs, baseline (1/4)

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

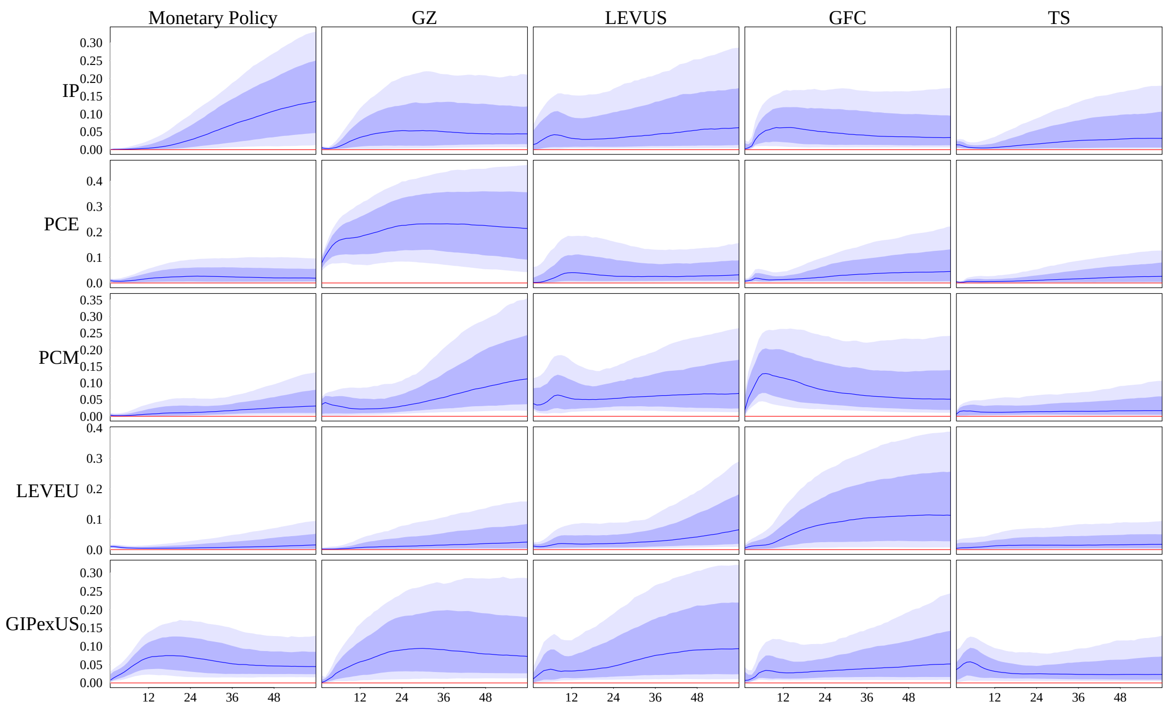


Figure 9: HB-SVAR Variance Decomposition: Global VARs, baseline (2/4)

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

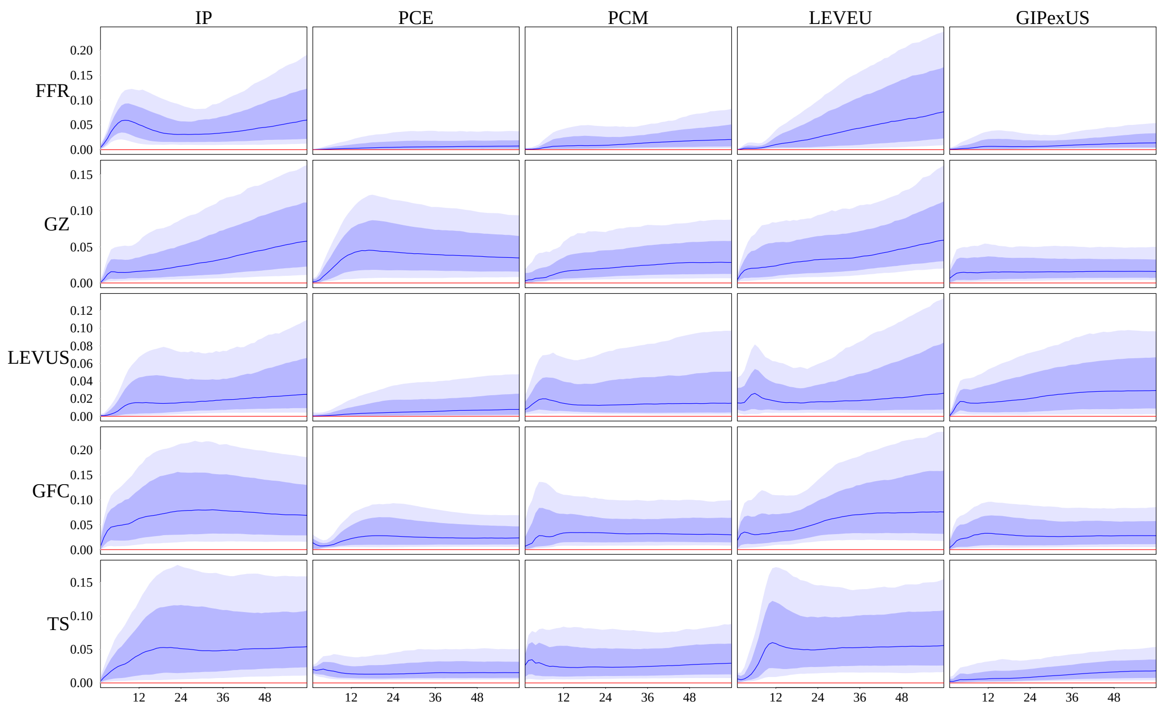


Figure 10: HB-SVAR Variance Decomposition: Global VARs, baseline (3/4)

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

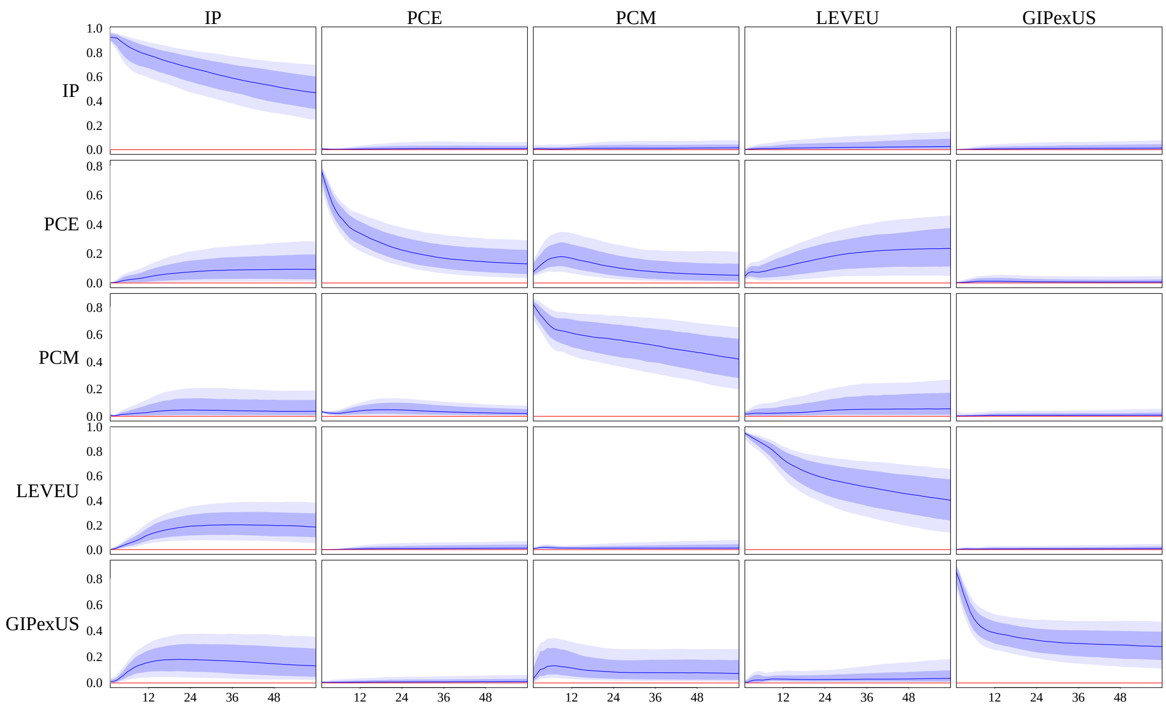


Figure 11: HB-SVAR Variance Decomposition: Global VARs, baseline (4/4)

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

The importance of shocks to GZ, TS, leverage and GFC in explaining dynamic movements in U.S. and global financial variables 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.

5.2 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 a 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 a 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 12. 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 early sample period through the mid-1990s.[12] 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,

[12] 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.

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.

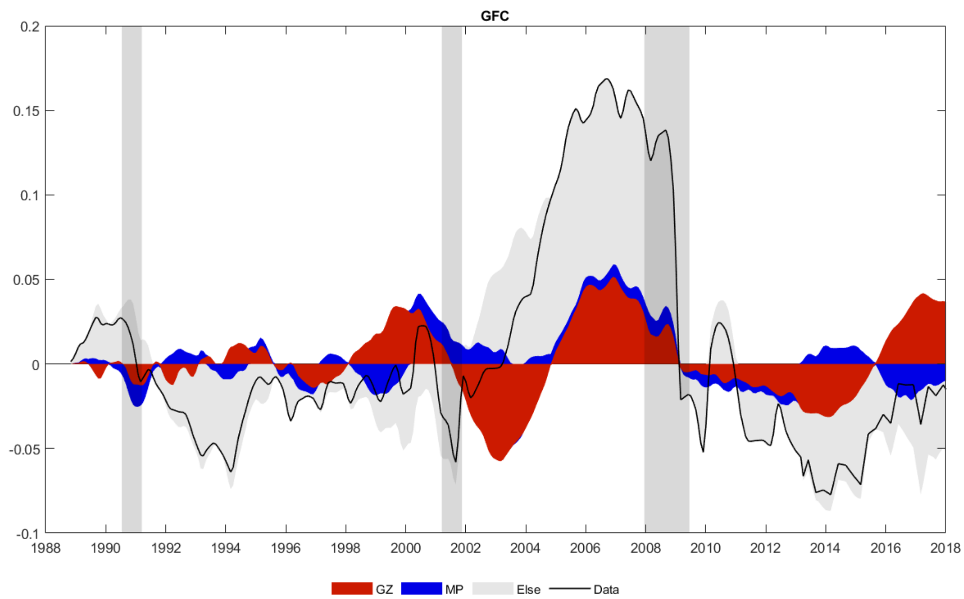


Figure 12: HB-SVAR Historical Decomposition: Global Financial Cycle and Financial Shocks

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.

5.3 Global Financial Cycle in Flows

Accounts of the global financial cycle such as Miranda-Agrippino et al. (2020) convincingly document a global cycle in capital *flows* in addition to the one in risky asset prices that has been the focus of our attention so far. To investigate drivers of this aspect of the global cycle, we replace the Miranda-Agrippino & Rey (2020b) GFC measure with the Global Inflows all Sectors (GLBIF) variable described above.

6 Robustness

6.1 Monetary Policy Measures

The Federal funds interest rate was stuck at the zero lower bound during 2008–2015. Because of this, it is useful to examine the robustness of our conclusions to using alternative measures of the monetary policy indicator. We test robustness using either the shadow rate of Wu & Xia (2016), the "policy news" shock of Nakamura & Steinsson (2018), forward guidance shock of Swanson (2021), or the "unified" measure of Bu et al. (2021), in place of FFR.[13] These alternative measures can alleviate concerns associated with the zero lower bound by exploiting information in the yield curve.

The estimated impulse response functions to each of the ten shocks are presented in Figure 13a. We focus on the responses of key outcome variables: GFC, GZ, TS, and LEVUS. Each panel displays point estimates for each of the five measures of U.S. monetary policy. The results imply a lot of robustness across measures, in particular with regard to our estimates of interest. As seen in the top row, the responses of the GFC factor to either monetary policy shocks or GZ shocks are highly similar in the five cases. Furthermore, as seen in row (2), the amplification mechanism implied by a significant negative response of GZ to GFC shocks is similarly evident irrespective of which measure of U.S. monetary policy is used.

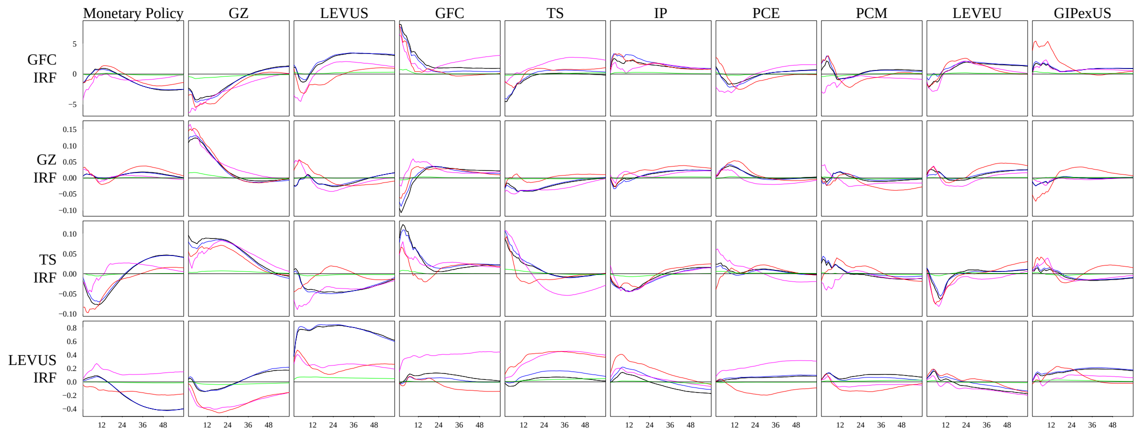
Turning to the analogous variance decompositions depicted just below in Figure 13b, we again see that our conclusions from the baseline model are largely valid across each of the five measures of U.S. monetary policy included in the VAR. Examining the accounting of the GFC factor depicted in the top row of the lower panel, we observe some non-trivial differences. For example, when using the Bu et al. (2021) measure (and hence sample period beginning in 1995), monetary policy shocks account for slightly more than 10% of the GFC forecast error variance on impact and overall a larger share than in the case of the other monetary policy shock measures. Similarly, in this case and the one with the Swanson (2021) FG shock, GZ shocks account for a larger share of the VDC of GFC in the short run than is the case using any of the other three monetary shock measures.

6.2 Regime Choices

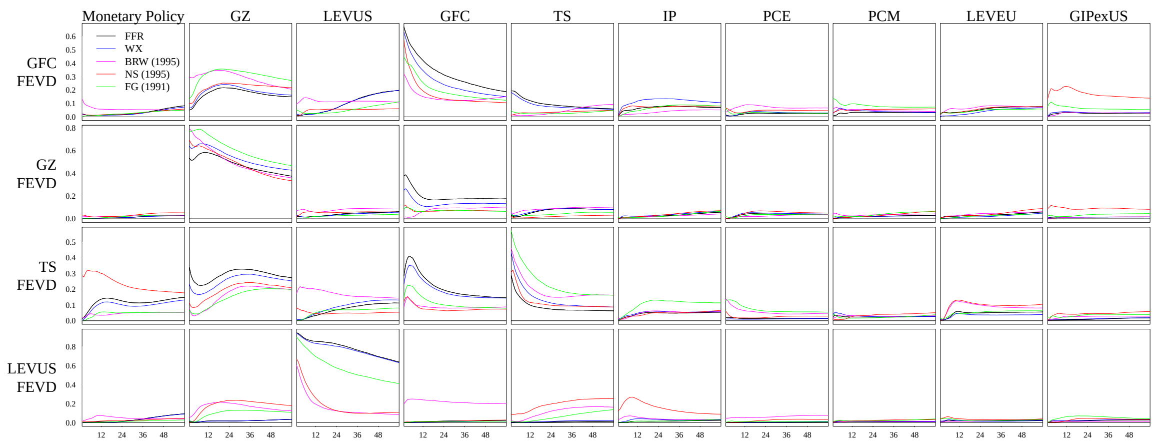
As noted above, heteroscedasticity in the disturbances of our VAR equations is a crucial identifying assumption. It is thus useful to know how those time-varying variances differ over alternative regime choices and whether or not those differences alter our conclusions.[14] Recalling that our baseline estimation essentially followed the Brunnermeier et al. (2021) choice of regimes, based on characteristics of U.S. monetary policy, our alternatives are based on a historical partition of global events shown in Table A.2. The variance decomposition results based on the alternative

[13] Furthermore, for the purpose of explaining a transmission channel involving reactions of foreign central banks, we examine a specification that *includes* (rather than replaces FFR) the ECB deposit facility rate in the next section.

[14] Though on this point, as Sims (2021) notes, "If we assume that relative variances are constant within regimes, but in fact they change within as well as across regimes, possibly because the dating of the regimes is inaccurate, the coefficients are nonetheless usually estimated consistently."



(a) Impulse Responses



(b) Variance Decompositions

Figure 13: Various Measures of Monetary Policy Shocks

regimes are summarized in Panel A of Table 6. We report the variance shares of GZ and baseline U.S. monetary policy shocks in accounting for the GFC. Although there are some differences in magnitudes across regimes, our qualitative conclusions are largely unchanged.

Table 6: Variance Decomposition of GFC with Different Specifications (%)

Shocks to:	**Monetary Policy**					**GZ**				
Horizons	**1**	**6**	**12**	**24**	**36**	**1**	**6**	**12**	**24**	**36**
Panel A: Alt. Regimes										
Baseline	4.35	1.64	2.28	3.39	8.07	6.12	11.73	17.32	22.45	21.11
Alt. Regime 1	2.60	1.03	2.44	3.31	7.26	10.59	12.61	10.67	8.02	6.77
Alt. Regime 2	13.20	8.35	5.76	4.79	7.81	9.42	13.87	14.90	14.44	13.30
Panel B: Alternative Specifications										
EBP	2.20	0.95	1.39	1.88	3.46	6.46	6.06	14.61	22.16	20.44
ECB Rate	5.58	3.52	2.92	3.59	4.94	2.42	6.35	8.37	8.90	8.52
WUI	3.28	1.73	1.46	1.95	3.62	1.90	7.25	10.83	12.17	10.78
TFU	2.15	1.11	1.06	1.47	3.76	8.93	12.46	12.36	12.47	11.67
Risk Aversion	1.50	0.80	0.85	1.74	4.17	2.19	7.60	10.73	10.73	9.53
EER	0.91	0.44	0.63	1.44	3.61	5.80	11.14	15.11	16.49	14.66
Panel C: Alternative Identification Procedures										
SV-SVAR	0.25	0.58	0.96	2.47	5.22	44.25	42.94	41.85	33.67	25.41
Cholesky	1.96	1.78	1.95	1.42	3.60	37.78	33.38	28.56	24.67	21.96
Panel D: Excluding the GZ index										
Shocks to:	**Policy Rate (FFR)**					**GFC**				
Excluding GZ	1.47	0.71	1.04	1.46	3.18	80.67	67.45	57.76	46.78	40.00

Estimates in each row are based on models with different specifications. In Panel C, "SV-SVAR" indicates Bertsche & Braun (2022)'s SV-SVAR method, with 7 variables (our baseline but excludes PCM, LEVEU and GIPexUS, which show weak evidence of ARCH effect. "Cholesky" indicates a Choklesy VAR with the high-frequency surprise in the three month ahead Fed Funds future rate (FF4) ordered first, followed by IP, GIPexUS, PCM, PCE, LEVUS, LEVEU, TS, GZ, GFC; estimated with 10 lags over 1990M2-2019M1.

6.3 Further Robustness Checks

We conduct many other extensions and robustness checks, in order to validate our main findings. First, we replace GZ spreads with the excess bond premium—a measure of U.S. credit market sentiment computed from deviations of corporate bond prices relative to the measured default risk (Gilchrist & Zakrajšek 2012). Panel B (Row 3) of Table 6 shows the variance decompositions with the EBP in place of the GZ spreads. 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 points to the significant role of financial institutions in influencing the Global Financial Cycle.

Uncertainty 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. In addition, the dollar appreciates, capital flows out of the foreign country, and the foreign currency excess return increases.[15] We estimate the HB-SVAR models 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 Panel B (Row 6-7) of Table 6, our baseline conclusions on the relative importance of different shocks are robust.

Including auxiliary variables We estimate versions of the ten-variable model including auxiliary variables, one at a time, and present the FEVD results in Panel B of Table 6. These variables include global risk aversion estimated by Miranda-Agrippino & Rey (2020b) and the trade-weighted U.S. dollar exchange rate. Results are reported in Panel B (Row 10-13) of Table 6. Our conclusions regarding the the relative importance of GZ spreads in driving the GFC factor are confirmed.

Excluding the main variable 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? We find that impulse responses are quite similar to the baseline results for all other variables. We report the FEVD results in Panel C of Table 6. 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 is not replaced by other variables.

[15] They use a two-country dynamic macro model featuring balance-sheet constrained financial intermediaries. The main exogenous driving force 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)).

6.4 Alternative Identification Approach: Stochastic Volatility SVAR

The Brunnermeier et al. (2021) framework allows us to estimate the effects of multiple shocks without having to rely on timing or sign restrictions. As a robustness check, we implement the method of Bertsche & Braun (2022), who show that SVARs can be identified by exploiting stochastic volatility, thus also sidestepping the potential pitfalls associated with traditional VAR identification tools. 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,

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

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

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.[16]

As seen in Figure A.1, the SV-SVAR model generates similar impulse responses to the monetary policy and GZ shocks as does the HB-SVAR model. A U.S. monetary policy tightening leads to a drop in IP, TS, GFC, and LEVUS; the GZ response is insignificant. In response to GZ shocks, the GFC factor declines substantially and immediately, U.S. IP falls in the first year, while leverage, term spreads, and PCE fall slightly. Monetary policy loosens in response to the GZ shock. As seen in Panel C of Table 6. GZ shocks are the primary driver of the global financial cycle factor, accounting for upwards of 40% of the forecast error variance of GFC at short horizons and well over 20% in the long run. U.S. monetary policy shocks do not account for a significant fraction at any horizon. Similar results are found in a Cholesky VAR in the ten baseline variables, as described in the table.

[16] According to the ARCH tests (part of the "mild assumptions") in Table A.1, the PCM, LevEU and global output residuals do not exhibit significant heteroscedasticity, so those variables are excluded.

7 Channels

7.1 U.S. Credit Spreads, Monetary Policy, and the Global Financial Cycle

As seen above, a shock to the U.S. corporate bond spread (GZ) leads to a significant and immediate decline in the global financial cycle (GFC) factor. This suggests that a deterioration in U.S. financial conditions, captured by rising corporate bond spreads, can quickly spill over to global financial markets, causing a downturn in the global financial cycle. The VDC confirms that GZ shocks are a significant driver of the GFC factor, especially at short horizons. When U.S. financial conditions deteriorate (GZ rises), it triggers a global risk-off sentiment and/or stress in the global dollar funding market, leading to a decline in the GFC factor. Several economic channels could give rise to the initial GFC response to a GZ impulse. These mechanisms are all rooted in the centrality of U.S. in global financial network, allowing corporate bond market shocks in the U.S. to quickly propagate to the global financial cycle.

a. Risk appetite and sentiment U.S. corporate bond spreads are often viewed as a barometer of overall risk sentiment in financial markets. A sharp rise in GZ can signal a deterioration in risk appetite and a flight to safety. This change in sentiment can quickly spread to global markets, leading to a broad-based sell-off in risky assets and a decline in the GFC factor. The contribution of U.S. leveraged financial institutions in driving the global financial cycle can also originate from institutions' additional role of a coordination device for shifts in global risk perceptions.[17] To examine the role of risk sentiment in driving our main results, we replace GZ in our baseline model with the risk appetite measure of Bauer et al. (2023). In Figure 14, we compare the impulse responses to a positive GZ shock in the baseline model and to a negative risk appetite shock in the new model. The responses of GFC, FFR, and LevUS—and TS in the long run—are quite close in the two cases.

[17] 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 to 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. 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.

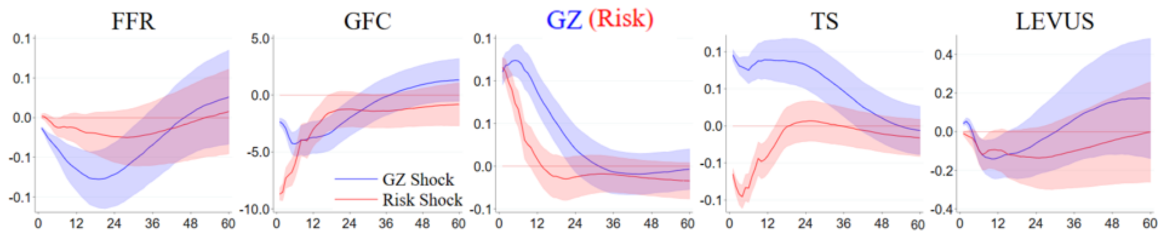


Figure 14: Responses to (positive) GZ Shocks and to (negative) Risk Appetite Shocks

Note: Impulse responses of from two versions of our HB-SVAR. First, the response to a GZ shock in the baseline case and second to a **(negative)** Bauer et al. (2023) risk appetite shock in a specification in which risk appetite replaces GZ. The shaded area represents 68% bands.

b. Amplification from Fed policy and cross-border policy spillovers? If rising GZ prompts the Federal Reserve to tighten monetary policy or provide less accommodative guidance, it could lead to a broader tightening of global financial conditions, given the central role of U.S. monetary policy in driving global liquidity. Moreover, other central banks may follow suit to prevent capital outflows and currency depreciation, further amplifying the global financial tightening. As seen in Figure 2, however, the response of FFR to GZ shocks is negative (Fed loosens), as noted above. We further investigate monetary policy spillover channels by including the ECB's Deposit Facility rate in the baseline VAR. We find that the ECB policy rate responds positively and significantly to a Fed tightening, as expected. In addition, we find that the response of GZ to an ECB tightening is small but positive and significant in the short run. The GFC factor response to an ECB tightening is negative and significant in the short run, though it is also small. Thus, foreign (ECB) monetary policy responses to a Fed tightening have a small but significant amplification effect alongside the direct effect of U.S. monetary policy in driving the global financial cycle.[18] But there is no feedback loop working between GZ shocks and Fed monetary policy.

c. Financial spillovers through global banks and investors Many global banks and investors have significant exposure to the U.S. corporate bond market. When GZ rises, these institutions may suffer losses or face tighter funding conditions, forcing them to reduce their risk exposure and lending globally. Moreover, as U.S. corporate bonds are widely used as collateral in global financial transactions, a decline in their value (higher GZ) can lead to margin calls and fire sales, amplifying the global financial tightening. Figure 2 indicates that there is a slight deleveraging of U.S. banks in response to positive GZ shocks, though it is small (and even smaller with EU banks).

d. U.S. dollar funding and global liquidity The U.S. dollar plays a dominant role in global

[18]The Federal Funds interest rate does not respond significantly to the ECB monetary policy shock, nor does the ECB policy rate respond significantly to GZ shocks.

finance, and many international corporations and banks rely on U.S. dollar funding markets, which are closely linked to the corporate bond market. A rise in GZ can indicate a tightening of U.S. dollar funding conditions, which can spill over to global markets, reducing liquidity and increasing borrowing costs for international entities.

e. Trade and investment linkages The U.S. is a major trading partner and source of foreign direct investment for many countries. If rising corporate bond spreads indicate growing financial stress in the U.S. corporate sector, it could lead to reduced U.S. import demand and investment outflows. These real economic spillovers can contribute to a global slowdown, which is often associated with a deterioration in the GFC. We leave for future work exploration of this channel.

7.2 GZ-GFC Feedbacks

Our findings highlight a feedback mechanism between corporate bond spreads and the global financial cycle factor. As discussed above, we find that a widening GZ shock leads to a significant and immediate decline in the global financial cycle (GFC) factor and that GZ shocks account for a notable fraction of the GFC's forecast error variance. This indicates that credit market stress in the U.S. spills over to global financial markets, especially at short horizons. Moreover, the IRFs show that a positive shock to the GFC factor leads to a significant narrowing of the GZ spread, while the VDCs indicate that GFC shocks account for a non-trivial portion of the variance in GZ. This suggests that a downturn in the global financial cycle can feed back into U.S. credit markets, causing U.S. corporate bond spreads to widen.

This GZ-GFC relationship implies a feedback loop that produces amplification effects. When U.S. corporate bond spreads widen, it triggers broad declines in global asset prices. This global financial tightening can then feed back into the U.S., further widening corporate bond spreads, as evidenced in the 2008 global financial crisis and at the onset of the COVID pandemic. Several mechanisms exist that could account for the feedback of a GFC shock to the U.S. GZ spread.

a. Risk appetite and sentiment during a global financial downturn, global investors may retreat from risky assets, including U.S. corporate bonds, reducing liquidity in the U.S. bond market. A "flight to quality" amid uncertainty widens GZ spreads.

b. Interaction between financial markets and real economy To the extent that a global financial downturn foreshadows protracted output declines (as implied by the responses of U.S. and global output in GFC shocks in column (4) of Figure 2), it might undermine the fundamentals of

U.S. corporations, as perceived by investors, thereby widening their credit spreads.

c. Reliance on international funding market Global financial stress may tighten financial conditions for U.S. banks and corporations that rely on international funding markets, exacerbating the initial shock. Following a negative GFC shock, the accompanied U.S. and EU bank deleveraging, shown in Figure 2, indicate reduced market liquidity and credit availability, raising the cost of borrowing for U.S. corporations.

Taken together, our findings suggest a potential two-way feedback loop between U.S. corporate bond markets and the global financial cycle, where shocks to one can amplify and prolong the response of the other. This underscores the centrality of U.S. in global financial markets and the potential for amplification effects.

7.3 Domestic Credit Expansion

Gourinchas & Obstfeld (2012) argue that expansion of domestic credit—which they regard as a proxy for leverage—played the key role in precipitating financial crises in the 20^{th} century. As noted in Table 1, the authors' preferred measure of domestic credit consists of the total claims of depository corporations minus net claims on central government. Their estimated logit model of financial crises indicates that past years' domestic credit expansion was a robust and significant predictor of financial crises in both emerging and advanced economies. The Gourinchas & Obstfeld (2012) measure is therefore a logical candidate to consider as a driver of the global financial cycle. In Figure 15 we depict the impulse responses and variance decompositions to a shock to global domestic credit in place of GZ. A positive shock leads to a persistent increase in the leverage of U.S. and EU banks, consistent with the Gourinchas & Obstfeld (2012) interpretation of their measure, and a rise in output and prices in spite of a Fed monetary policy tightening. Global asset prices (GFC) rise persistently and the U.S. term premium narrows. As seen in the bottom rows of the figure, GDCRT shocks account for around 20% of the forecast error variance of several variables, with the exception of the Federal Funds interest rate, where the contribution is close to zero. Although our estimates are silent on crisis probabilities, they imply that the global domestic credit indicator of financial crises is another important driver of the global financial cycle factor of Miranda-Agrippino & Rey (2020b).

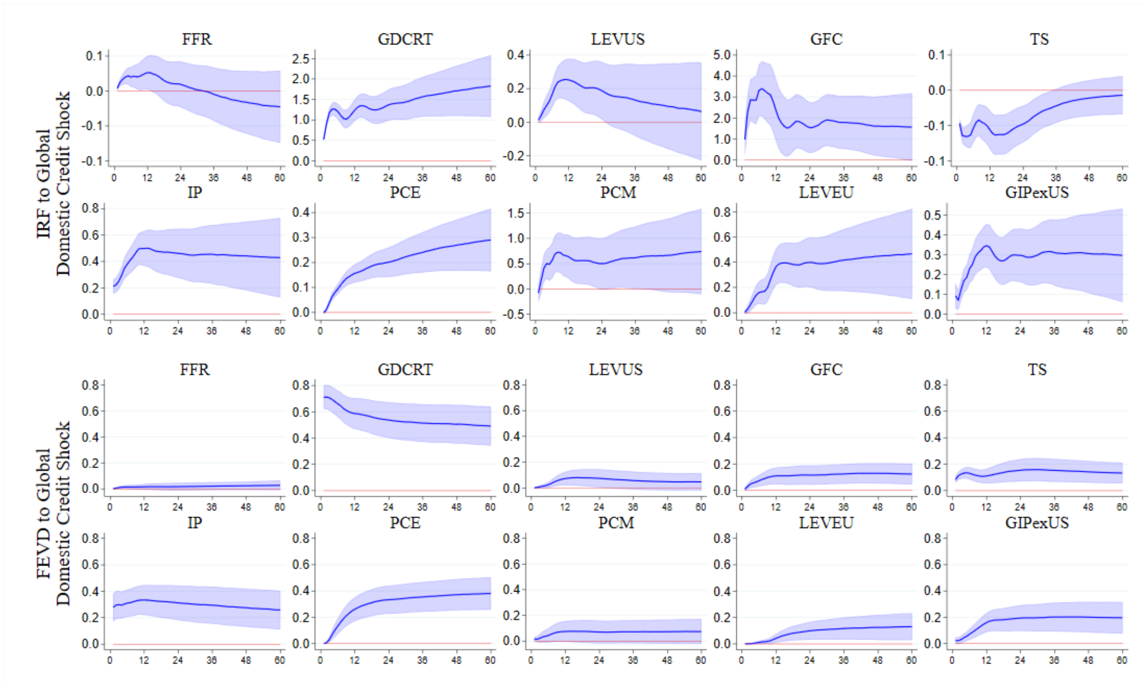


Figure 15: Responses and Variance Decompositions to Global Domestic Credit Shocks

7.4 Centrality of the U.S. Dollar

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 has been defined by the centrality of the U.S. dollar.[19] Although broad international use of the U.S. dollar generates significant benefits globally, arising from economies of scale and network effects, 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.[20] Central insights from models of financial interactions can be extended to a global financial network characterized by high interconnectedness through global integration

[19] 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, and a 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%).

[20] Bodenstein et al. (2023) develop and estimate a macroeconomic model of the world economy featuring time variation in global preference for dollar-denominated safe assets. These global flight-to-safety shocks emerge as the important drivers of fluctuations in world GDP.

and the dominant international role of the U.S. dollar.[21] 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 centers dominate the world of financial investment, representing the only pole in the global financial network.

Transmission Effects on Countries with Fixed versus Floating Exchange Rates

Fundamental to the notion of "dilemma not trilemma" in Rey (2013) is that due to the outsized global role of the U.S. dollar, countries lack sovereignty in setting monetary policy—irrespective of their exchange rate regime— unless they enact capital controls. An important finding of Miranda-Agrippino & Rey (2020b) is that countries which adopt a floating exchange rate regime are as equally exposed to U.S. monetary policy shocks as other countries. Miranda-Agrippino & Rey (2020b) restrict the sample to include only "independently floating" countries, using the IMF's de-facto classification at https://www.imf.org/external/np/mfd/er/2008/eng/0408.htm. Their impulse responses indicate that the magnitude of the contraction in credit variables to U.S. monetary policy shocks for the floaters is very similar to that obtained using the full sample of countries.[22]

Against this backdrop, we explore evidence on the role of exchange rate regime in an extension of the baseline HB-SVAR model. We begin by constructing a GFC-like index for the countries designated by Miranda-Agrippino & Rey (2020a) as independently floating.[23] 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. Additionally, for another 48 countries with MSCI prices available and not classified as "floaters", we retrieve the annual peg indicator of Klein & Shambaugh (2008) from Jay C. Shambaugh's website. Then, for each point in time, we compute the "MSCI Fixers" as the log of the average MSCI prices for countries who have the peg indicator equal to one.

In Figure 16, we depict the IRFs from a comparison of samples of countries whose exchange rate regimes are labeled "fixed" and those labeled "independently floating". According to the first

[21] Allen & Gale (2000), Battiston et al. (2012), Elliott et al. (2014), Cabrales et al. (2014), Acemoglu et al. (2015)

[22] 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."

[23] There are 27 countries, including Australia, Austria, Belgium, Brazil, Canada, Chile, Czech Republic, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovenia, South Africa, Spain, Sweden, Turkey, and the UK.

panel, there is not much difference between floaters and fixers in the spillover effects of U.S. monetary policy shocks. Risky asset prices decline in response to a tightening of Fed monetary policy to about the same degree, irrespective of exchange rate regime. Likewise, following a positive GZ shock, the IRF of MSCI (floaters) exhibits a pattern similar to that of MSCI (fixed), but with floaters actually responding by slightly *more*. The same can be said for shocks to leverage and U.S. term premium. Honing in on the contrast between MSCI (fixed) and MSCI (floaters) for the other shocks in the baseline model, we see that the only significant piece of evidence that floating exchange rate regimes insulate countries from foreign shocks comes from shocks to U.S. output (panel 6). Thus, in line with Miranda-Agrippino & Rey (2020b), we conclude that a floating exchange rate regime does not completely insulate countries from external shocks, consistent with a world of dollar centrality.

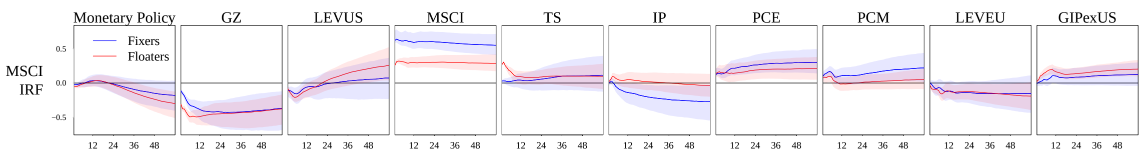


Figure 16: Impulse Responses to all shocks of the MSCI (Fixers) vs. MSCI (Floaters)

8 Conclusion

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 other important barometers accounting for strains in the global financial system? Does Fed monetary policy or these other barometers act as amplification mechanisms for shocks?

We initiate a first attempt to rank a large number of shocks in their contributions to 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. Furthermore, we assess amplification mechanisms. Importantly, we show that shocks to (i) U.S. corporate bond spreads—especially, the excess bond premium that reflects the pricing of defaults rather than their risk— (ii) U.S. term premium, and (iii) leverage, emerge as the most powerful drivers of the global financial cycle. By comparison, contributions of Fed monetary policy shocks to global financial cycles appear modest, consistent with monetary policy being *reactive* to changes in underlying economic and financial conditions. Our results suggest that the outsized U.S. influence in shaping GFC may be rooted in the centrality of U.S. financial intermediaries and the dollar rather than the Fed itself. This interpretation is consistent with—and indeed reflective of—features that have characterized the global financial landscape over recent decades.

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