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US MONETARY POLICY AND THE GLOBAL FINANCIAL CYCLE

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ABSTRACT

We analyze the workings of the "Global Financial Cycle." We study the effects of monetary policy of the United States, the center country of the international monetary system, on the joint dynamics of the domestic business cycle and international financial variables such as global credit growth, cross-border credit flows, global banks leverage and risky asset prices. One global factor, driven in part by US monetary policy, explains an important share of the variance of returns of risky assets around the world. We find evidence of large financial spillovers from the hegemon to the rest of the world.

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1 Introduction

Observers of balance of payment statistics and international investment positions all agree: the international financial landscape has undergone massive transformations since the 1990s. Financial globalization is upon us in a historically unprecedented way, and we have probably surpassed the pre-WWI era of financial integration celebrated by Keynes in "The Economics Consequences of the Peace". Against this changing landscape, the role of the United States as the hegemon of the international monetary system has largely remained unchanged, and has long outlived the end of Bretton Woods as emphasized in e.g. Farhi and Maggiori (2017) and Gourinchas and Rey (2017). The rising importance of cross-border financial flows and holdings has been documented in the literature;[1] what has not been explored as much, however, are the consequences of financial globalization for the workings of national financial markets and for the transmission of US monetary policy beyond the national border. How do international flows of money affect the international transmission of monetary policy? What are the effects of global banking on fluctuations in risky asset prices in national markets, and on credit growth and leverage in different economies? Using quarterly data covering the past three decades, this paper's main contribution is to estimate the global financial spillovers of the monetary policy of the United States, the current hegemon of the international monetary system.

There is a large literature on the domestic transmission of monetary policy. In a standard Keynesian or neo-Keynesian world, output is demand determined in the short-run, and monetary policy stimulates aggregate consumption and investment. In such a world, there are no first order responses of either spreads or risk premia (see Woodford, 2003 and Gali, 2008 for classic discussions). In models with frictions in capital markets, on the other hand, expansionary monetary policy leads to an increase in the net-worth of borrowers, be they either financial intermediaries or firms. In turn, this leads to an increase in lending, and in aggregate demand. This is the *credit channel* of monetary policy (Bernanke and Gertler, 1995). Other papers have instead analyzed the *risk-taking channel* of monetary policy (Borio and Zhu, 2012; Bruno and Shin, 2015a; Coimbra and Rey, 2017) where financial intermediation plays a key role, and loose monetary policy

[1] See e.g. Lane and Milesi-Ferretti, 2007 and, for a recent survey, Gourinchas and Rey (2014).

relaxes leverage constraints. These channels are complementary to one another. In this paper, we explore the *international* transmission of monetary policy that occurs through financial intermediation and global asset prices, an area that has been largely neglected by the literature.[2]

Empirically, we analyze the dynamic interactions between US monetary policy, international financial markets and institutions, and credit and financial conditions in the rest of the world using a Bayesian VAR. A standard selection of variables capturing domestic business cycle fluctuations and consumer sentiment is augmented with a set of variables summarizing the evolution of global credit flows, global leverage, and a collection of financial indicators. In particular, we include a global factor in risky asset prices, the excess bond premium of Gilchrist and Zakrajšek (2012), the term premium, and global stock market volatility. We test for the existence of, and estimate a global factor summarizing the common variation in a large and heterogeneous collection of risky asset prices traded around the globe.

We find evidence of powerful financial spillovers of the monetary policy of the hegemon to the rest of the world. When the US Federal Reserve tightens, domestic output, investment, consumer confidence, real estate investment and inflation all contract. But, importantly, we also see significant movements in international financial variables: the global factor in risky asset prices goes down, spreads go up, global domestic and cross-border credit go down very significantly, and leverage decreases – first among US broker-dealers and global banks in the Euro area and the UK, then among the broader banking sector in the US and in Europe. We also find evidence of an endogenous reaction of monetary policy rates in the UK and in the Euro area. Hence, our results point to the existence of a "Global Financial Cycle" (see Rey, 2013), i.e. fluctuations in financial activity on a global scale. They are consistent with a powerful transmission channel of US monetary policy across borders via financial conditions as reflected in asset prices, credit flows, leverage of banks, risk premia, volatility, and the term spread. In short, we show that the monetary policy of the hegemon influences aggregate risk appetite in international financial markets.

The importance of international monetary spillovers and of factors such as the world

[2]For a longer discussion see Rey (2016).

interest rate in driving capital flows has been pointed out in the seminal work of Calvo et al. (1996).[3] Some recent papers have fleshed out the roles of intermediaries in channeling those spillovers. Cetorelli and Goldberg (2012) use balance sheet data to study the role of global banks in transmitting liquidity conditions across borders. Using firm-bank loan data, Morais et al. (2015) find that a softening of foreign monetary policy increases the supply of credit of foreign banks to Mexican firms. Using high-quality credit registry data combining firm-bank level loans and interest rates data for Turkey, Baskaya, di Giovanni, Ozcan and Ulu (2017) show that increased capital inflows, instrumented by movements in the VIX, lead to a large decline in real borrowing rates and a sizeable expansion in credit supply. Interestingly, they find that the increase in credit creation goes mainly through a subset of the biggest banks. Bernanke (2017) provides a thorough discussion of international financial spillovers of US monetary policy.

Our empirical results on the transmission mechanism of monetary policy via its impact on risk premia, the term spread, and volatility are related to the results of Gertler and Karadi (2015) and Bekaert, Hoerova and Duca (2013) obtained in the domestic US context. Our paper also contributes to the recent literature which underlines the importance of leverage and credit growth as determinants of financial instability (Gourinchas and Obstfeld (2012); Schularick and Taylor (2012); Jordà, Schularick and Taylor (2015); Kalemli-Ozcan, Sorensen and Yesiltas (2012)).[4] A small number of papers have analyzed the effect of US monetary policy on leverage and on the VIX (see Rey (2013); Passari and Rey (2015) and Bruno and Shin (2015b)). But these studies rely on limited-information VARs (four to seven variables) and are therefore unable to study the joint dynamics of real and financial variables, both in a domestic and international context.[5]

The present paper differs from the above literature in important ways. The use of a medium-scale Bayesian VAR allows, we believe for the first time, the joint analysis of financial, monetary and real variables, in the US and abroad. Studying the joint dynam-

[3]A subsequent literature has echoed and extended some of these findings (see Fratzscher, 2012; Forbes and Warnock, 2012; Rey, 2013).

[4]The Basel Committee has formally introduced the credit to GDP gap as one of the main early warning indicators for macroprudential policy in the Basel 3 framework.

[5]Most existing studies rely exclusively on Cholesky identification schemes to study the transmission of monetary policy shocks. It is unclear whether their results survive a more robust identification of monetary policy shocks. The problem of omitted variables that are relevant for the identification and transmission of monetary policy is also an important issue in small scale VARs.

ics of the domestic business cycle and the Global Financial Cycle would not have been possible without recent developments in the BVAR literature (see e.g. Bańbura et al., 2010; Giannone et al., 2015). Results are computed under two alternative identification schemes for the monetary policy shocks which deliver equivalent outcomes: a standard causal ordering, where the federal funds rate is the policy variable, and the remainder of the series are split among slow-moving and fast-moving ones as in e.g. Christiano et al. (1999); and an instrumental variable type identification, where a narrative-based measure of policy surprises in the spirit of Romer and Romer (2004) allows to identify the contemporaneous transmission coefficients without the need to impose potentially restrictive assumptions on the timing of the responses (Stock and Watson, 2012; Mertens and Ravn, 2013). We also evaluate responses obtained with a high-frequency identification scheme that uses federal funds futures to identify the shocks as in Gürkaynak et al. (2005).

Our results should help inform the theoretical modelling of financial spillovers of the hegemon monetary policy on the rest of the world. This is a topic of first order importance for issues ranging from the validity of the Mundellian trilemma, which describes the degree of monetary policy independence of open economies,[6] to financial stability and the "bunching" of financial crises around the world as suggested by the historical evidence gathered in e.g. Reinhart and Rogoff (2009); Schularick and Taylor (2012); Jordà et al. (2016).

In Section 2, we estimate a Dynamic Factor Model on world asset prices and show that one global factor explains a large part of the common variation of the data. Section 3 is the main part of the paper. We use a Bayesian VAR to analyze the interaction between US monetary policy and the Global Financial Cycle, and in particular on global banks' leverage, global credit creation, and on global cross-border credit flows and we establish the importance of the international financial spillovers of the US monetary policy. In Section 4 we use a simple theoretical framework featuring heterogeneous investors to interpret some of our results (Section 4.1), and microeconomic data on global banks to give evidence of their risk-taking behavior (Section 4.2). Section 5 concludes. Details on data, procedures, and additional results are in Appendixes at the end of the paper.

[6] See Obstfeld and Taylor (2017) for a discussion.

2 One Global Factor in World Risky Asset Prices

We specify a Dynamic Factor Model for a large and heterogenous panel of risky asset prices traded around the globe. The econometric specification, fully laid out in Appendix B, is very general, allowing for different global, regional and, in some specifications, sector specific factors.[7] We test for the number of global factors and find that the data support one; that global factor accounts for over 20% of the common variation in the price of risky assets from all continents.[8] The panel includes asset prices traded on all the major global markets, all major commodities price series, and a collection of corporate bond indices. The geographical areas covered are North America, Latin America, Europe, Asia Pacific, and Australia, and we use monthly data from 1990 to 2012, yielding a total of 858 different prices series.[9] The factor is plotted in Figure 1, solid line.

While in this instance we prefer cross-sectional heterogeneity over time length, we are conscious of the limitations that a short time span may introduce in the analysis we perform later in the paper. To allow more flexibility in that respect, we repeat the estimation on a smaller set, where only the US, Europe, Japan and commodity prices are included, and that goes back to 1975. In this case the sample counts 303 series. The estimated global factor for the longer sample is the dashed line in Figure 1. Similar to the benchmark case, for this narrower panel too we find evidence of one global factor. In this case, however, the factor accounts for about 60% of the common variation in the data. Factors are obtained via cumulation of those estimated on the stationary, first-differenced (log) price series, and are therefore consistently estimated only up to a scale and an initial value (see Bai and Ng, 2004, and Appendix B). This implies that positive and negative values displayed in the chart do not convey any specific information per se. Rather, it is the overall shape and the turning points that are of interest and deserve attention.

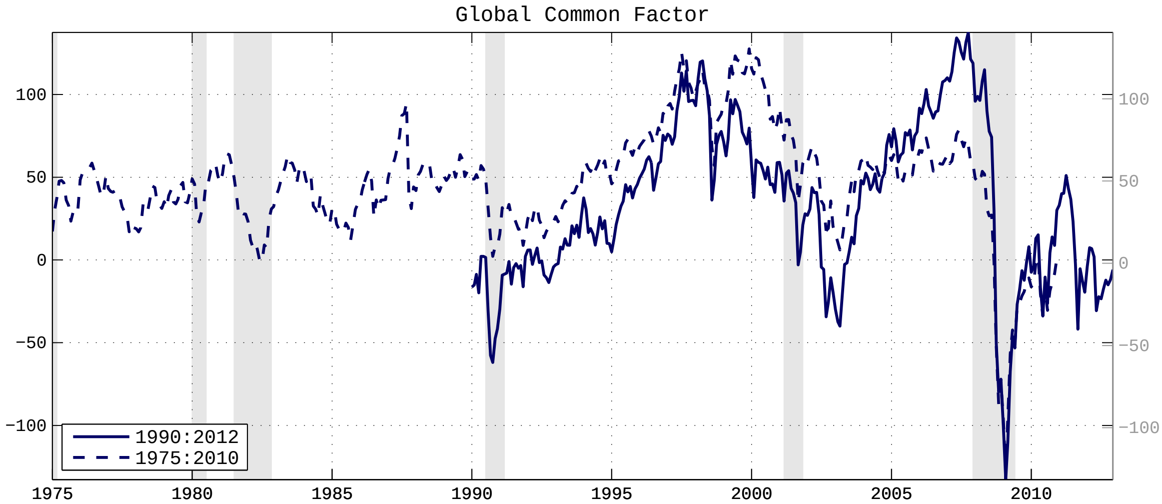
Figure 1 shows that the factor is consistent with both the US recession periods as

[7]A similar specification has been adopted by Kose et al. (2003); they test the hypothesis of the existence of a world business cycle and discuss the relative importance of world, region and country specific factors in determining domestic business cycle fluctuations.

[8]See Table B.2.

[9]All the details on the construction and composition of the panels, shares of explained variance, and test and criteria used to inform the parametrization of the model are reported in Appendix B. We fit to the data a Dynamic Factor Model (Stock and Watson, 2002a,b; Bai and Ng, 2002; Forni et al., 2000, among others) where each price series is modelled as the sum of a global, a regional, and an asset-specific component. All price series are taken at monthly frequency using end of month figures.

Figure 1: global factor in risky asset prices

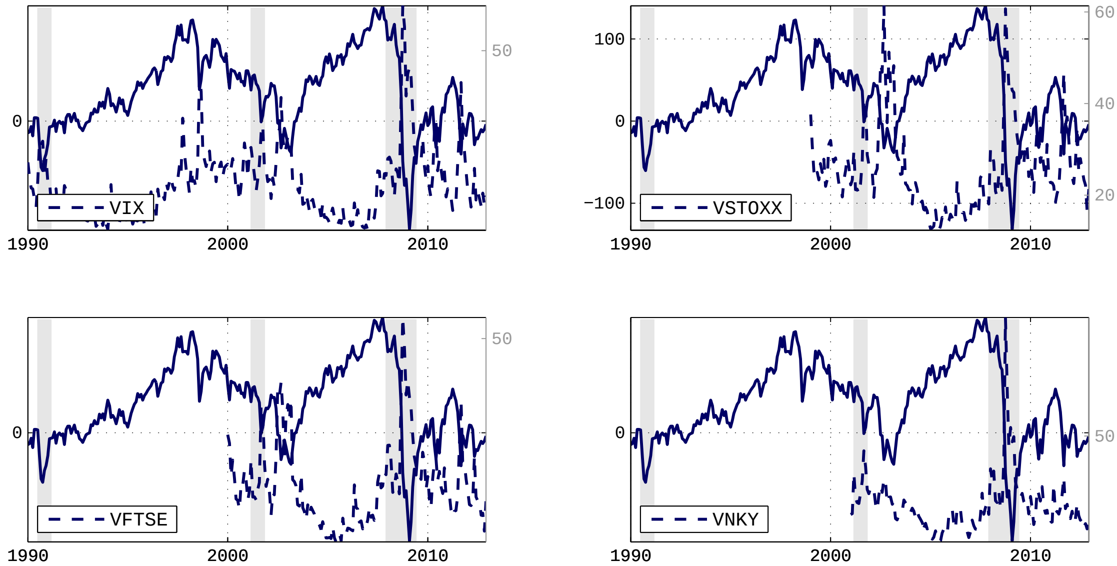


Note: The Figure plots the estimates of the global factor for the 1975:2010 sample (dotted line) together with the estimates on the wider, shorter sample 1990:2012 (solid line). Shaded areas denote NBER recession dates.

identified by the NBER (shaded areas), and with major worldwide events. The index declines with all the recession episodes but remains relatively stable until the beginning of the nineties, when a sharp and sustained increase is recorded. The increase lasts until 1997-1998 when major global events like the Russian default, the LTCM bailout and the East Asian Crisis reverse the increasing path associated with the build up of the *dot-com* bubble. The downward trend is inverted starting from the beginning of 2003 when the index increases again until the beginning of the third quarter of 2007. At that point, with the collapse of the subprime market, the first signals of increased vulnerability of the financial markets become visible. This led to an unprecedented plunge.

In a large class of asset pricing models, the global factor in risky asset prices reflects aggregate volatility scaled by the aggregate degree of effective risk aversion in the market (see e.g. the simple model we sketch in Section 4). In Figure 2 we highlight the co-movement of our factor with the "risk indices" associated to the markets included in our panel. Specifically, the VIX for the US, VSTOXX and VFTSE for Europe and the UK respectively, and VNKY for Japan. Volatility indices measure markets' implied volatil-

FIGURE 2: GLOBAL FACTOR AND VOLATILITY INDICES



Note: Clockwise from top-left panel, the global factor (solid line) together with major volatility indices (dotted lines): VIX (US), VSTOXX (EU), VNKY (JP) and VFTSE (UK). Shaded grey areas highlight NBER recession times.

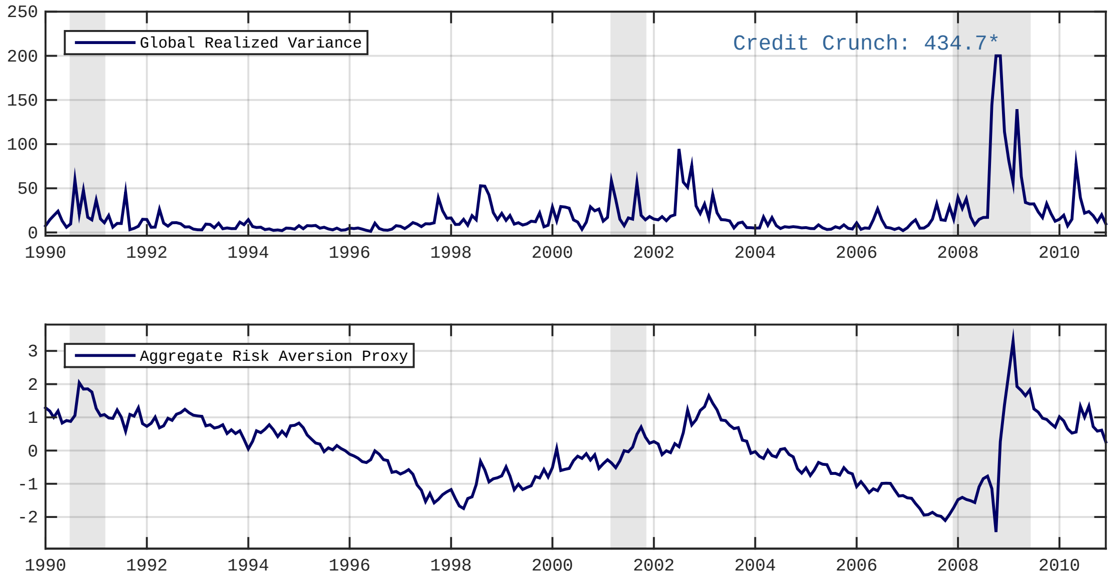
ity, and thus reflect both the expectation of future market variance, and risk aversion.[10] Therefore we expect all of them to be inversely related to our factor.[11] We note that the factor and the volatility indices display a remarkable common behaviour and peaks consistently coincide within the overlapping samples. While the comparison with the VIX is somehow facilitated by the length of the CBOE index, the same considerations easily extend to all other indices analyzed. Comparison with the GZ-spread of Gilchrist and Zakrajšek (2012) and the Baa-Aaa corporate bond spread (not reported) show that these indices also display some commonalities, even if the synchronicity is slightly less obvious than the one we find with respect to the implied volatilities.

Lastly, we separate the aggregate risk aversion and volatility components in our factor. The construction of our proxy for aggregate risk aversion is modelled along the lines of e.g. Bekaert et al. (2013) that estimate variance risk premia as the difference between a measure of the implied variance (the squared VIX) and an estimated physical expected

[10] These indices are typically regarded as an instrument to assess the degree of strains and risk in financial markets

[11] The estimated global factors are rotated such that they positively comove with prices; i.e. an increase in the index is interpreted as an increase in asset prices.

Figure 3: global factor decomposition

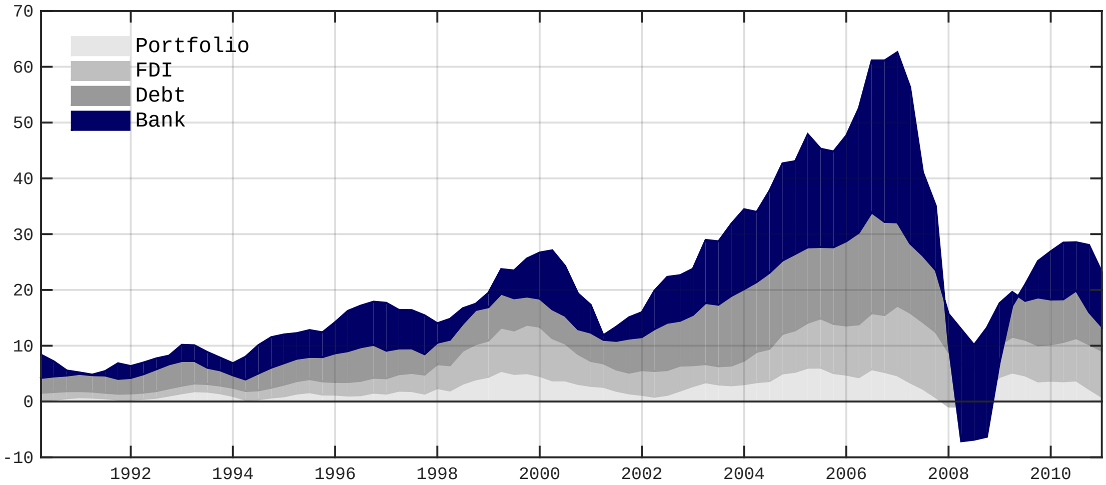


Note: [top panel] Monthly global realized variance measured using daily returns of the MSCI Index. The y axis is trimmed to enhance readability, during the credit crunch episode the index reached a maximum of 434.70. [bottom panel] Index of aggregate risk aversion calculated as (the inverse of) the residual of the projection of the global factor onto the realized variance. Shaded grey areas highlight NBER recession times. *Source:* Global Financial Data and authors calculations.

variance which is primarily a function of realized variances. First, we obtain an estimate of realized monthly global volatility using daily returns of the global MSCI Index.[12] Second, we calculate a proxy for aggregate risk aversion as the inverse of the centred residuals of the projection of the global factor on the realized variance. The results of this exercise are summarized in Figure 3. Our monthly measure of global realized variance is in the top panel, while the implied index of aggregate risk aversion is in the bottom panel. Very interestingly, the degree of market risk aversion that we recover from this simple decomposition is in continuous decline between 2003 and the beginning of 2007, and it decreases to very low levels, at a time where volatility was uniformly low and global banks were prevalent and may have been the "marginal buyers" in international financial markets. During that period, Shin (2012) documents the large share of banking flows in aggregate capital flows. Changes in regulation and consequences of the crisis have reduced the share of bank flows since 2008. We report data relative to aggregate capital

[12]We work under the assumption that monthly realized variances calculated summing over daily returns provide a sufficiently accurate proxy of realized variance at monthly frequency.

Figure 4: aggregate capital flows



Note: Global flows as a percentage of world GDP. Annual moving averages. *Source:* IFS Statistics.

flows as a percentage of world GDP in Figure 4. Interestingly, the timing of the surge of banking flows coincides with the decline in global risk aversion. Estimated aggregate risk aversion starts going up during 2007 then jumps up during the financial crisis with the banckruptcy of Lehman Brothers, and remains persistently at high levels.

3 Monetary Policy of the Hegemon and the Global Financial Cycle

In this section we study the international spillovers of US monetary policy. With the US dollar being the currency of global banking, monetary actions in the US may directly influence the cycle by altering the cost of funding for major global banks and hence their leverage decisions. US monetary policy also affects the pricing of dollar assets, both in the US and abroad, through a direct discount channel and/or by changing the type of marginal investors in international asset markets. Security-level evidence provided by Schreger et al. (2017) shows that firms who finance themselves in dollars are by and large the only ones able to attract a worldwide investors base. Furthermore, monetary conditions of the centre country can also be transmitted through cross-border capital flows or internal pricing of global banks, and influence the provision of credit outside US borders (see the corroborative evidence in Morais et al., 2015 for Mexico, and in Baskaya et al., 2017 for Turkey).

Fluctuations in asset prices are both cause and consequence of the procyclicality of financial leverage of global banks (see Section 4.2). Prolonged periods of loose monetary policy may reduce market uncertainty and credit/funding costs, with a boost to asset prices. Equally, rising asset prices may mask the fragile foundations of large and expanding global banks' balance sheets.[13] Hence, the hegemon monetary policy may well influence the global risk appetite of international markets.

To study the effects of US monetary policy on the Global Financial Cycle (GFC), we devise a single framework that permits analyzing the transmission of monetary policy above and beyond national borders. We augment the typical set of macroeconomic variables, output, inflation, investment, consumer sentiment and labor data, with global financial variables, and study their joint dynamics in a medium scale Bayesian VAR. There are a number of advantages that come with this choice. Most obviously, relying on a unique specification permits addressing the effects of US monetary policy on the GFC against the background of the response of the domestic business cycle. This acts both as a complement to the analysis, and as a disciplining device to ensure that the identified shock is in fact inducing responses that do not deviate from the standard channels of domestic monetary transmission. Moreover, the dimensionality and composition of the set of variables included in the VAR greatly reduce the problem of omitted variables that generally plagues smaller systems and is likely to invalidate the identification of the structural shocks.[14] The argument in favour of small-scale systems typically levers on the so-called curse of dimensionality: in an unrestricted VAR, the number of free parameters to be estimated rapidly proliferates with the addition of extra variables, and the risks of over-parametrization, and consequent high uncertainty around parameters estimates, are a legitimate source of concern. In particular, with macroeconomic data being sampled

[13]For a model where low funding costs lower risk aversion and increase leverage see Coimbra and Rey (2017)

[14]Bańbura et al. (2010) show that a medium-scale VAR of comparable size and composition to the one used in this paper is able to correctly recover the shocks and reproduce responses that match theoretical ones. Intuitively, the large degree of comovement among macroeconomic variables makes it possible for VARs of such size to effectively summarize the information contained in large VARs typically counting over hundred variables.

at low frequency and available over relatively short time spans, increasing the number of variables might in some instances simply not be feasible. Here we address this issue by estimating our VAR using standard macroeconomic priors (Litterman, 1986; Doan et al., 1983). The informativeness of the prior is determined as in Giannone et al. (2015). Intuitively, the solution to the problem achieved by Bayesian estimation comes from the use of informative priors which shrink the richly parametrized unrestricted VAR towards a more parsimonious naïve benchmark, thus effectively reducing estimation uncertainty.[15]

To the best of our knowledge, we are the first paper who can study the effect of the hegemon monetary policy on the joint dynamics of the US business cycle and of the GFC. To analyze the risk-taking or the credit channel of monetary policy, recent empirical contributions have exclusively employed small-scale VARs. Bekaert et al. (2013) studies the links between monetary policy and risk aversion in a domestic US context. They decompose the VIX index into an uncertainty component, driven by market variance, and a residual proxy for risk aversion. Using monthly data from 1990 to the onset of the 2007 crisis, they set up a VAR which adds to the VIX components the industrial production index and the real federal funds rate as the monetary policy variable. Bruno and Shin (2015b) and Rey (2013) put together small scale VARs with quarterly data, from the end of 1995 to the end of 2007, using the federal funds rate as the monetary policy variable, a measure of leverage, the VIX index and the US dollar real effective exchange rate or credit. A recursive Cholesky ordering is used for the identification of the monetary policy shocks.

Our analysis goes well beyond these papers by using a comprehensive set of financial and real variables and by allowing us to dissect the international dimensions of the financial spillovers. The variables that we include in the baseline BVAR specification are listed in Table 1 together with the transformations applied prior to the estimation, and ordering for the identification of the monetary policy shock in the standard case based on causal ordering. Unlike the previous papers, we also use an external instrument as a second identification scheme, which gives us a lot more confidence in the robustness of our results. The sample considered is 1980Q1 to 2010Q4, but we check robustness of our

[15]Alternatives include the use of factor models and sequential inclusion of individual variables to a core set which remains unchanged. This last method, however, renders comparison of impulse response functions problematic.

Table 1: variables in baseline var

ID	Name	Log	S/F	RW Prior
USGDP	US Real Gross Domestic Product	•	S	•
EUGDP	EA Real Gross Domestic Product	•	S	•
IPROD	Industrial Production Index	•	S	•
RPCE	US Real Personal Consumption Expenditures	•	S	•
RPFINR	Real private fixed investment: Non-Residential	•	S	•
RPFIR	Real private fixed investment: Residential	•	S	•
EMPLY	US Total Nonfarm Payroll Employment	•	S	•
HOUST	Housing Starts: Total	•	S	•
CSENT	University of Michigan: Consumer Sentiment		S	•
GDPDEF	US Implicit Price GDP Deflator	•	S	•
PCEDEF	US Implicit PCE Deflator	•	S	•
GDC	Global Domestic Credit	•	S	•
FEDFUNDS	Effective Federal Funds Rate		MPV	
GCB	Global Inflows To Banks	•	F	•
GCNB	Global Inflows To Non-Bank	•	F	•
BDLEV	US Broker Dealer Leverage		F	•
EURLEVQ	Euro area Global Banks Leverage		F	•
GBPLEVQ	UK Global Banks Leverage		F	•
EURATE	EA Policy Rate		F	
UKRATE	UK Policy Rate		F	
USDEUR	US Dollar to 1 Euro	•	F	•
USDGBP	US Dollar to 1 Sterling	•	F	•
TSPREAD	Term Spread		F	
GRVAR	MSCI Annualized Realized Variance	•	F	•
GFAC	Global Factor		F	•
GZEBP	GZ Excess Bond Premium		F	•

Note: The table lists the variables included in the baseline BVAR specification together with transformation applied, ordering, and selection for the random walk prior. S and F denote slow-moving and fast-moving variables respectively; MPV stands for monetary policy variable. The last column highlights the variables for which we assume a random walk prior. Robustness checks include specifications with USBLEV and EUBLEV (US and UK aggregate banking sectors leverage).

results to samples ending in 2009Q1 (excluding the zero lower bound period) and 2007Q2 (excluding the crisis episode).

3.1 Identification of the Monetary Policy Shocks

We present our results under two alternative identification strategies for the monetary policy shocks. In the first, standard case (see e.g. Christiano et al., 1999, and much of the existing literature), the identifying assumption is that it takes at least one quarter for the slow-moving variables such as output and prices (e.g. GDP and PCE deflator) to react to monetary policy shocks, and that the monetary authority only sees past observations of the fast-moving ones when making decisions. The identification in this case is practically achieved by computing the Cholesky factor of the residual covariance matrix of the VAR where variables enter following the order in Table 1. This identification scheme is useful to compare relevant subsets of our results with the existing (smaller) VARs reported in the literature.

The second identification scheme makes use of an external instrument to identify the monetary policy shocks (Stock and Watson, 2012; Mertens and Ravn, 2013). The intuition behind this approach to identification is that the mapping between the VAR innovations and the structural shock of interest can be estimated using only moments of observables, provided that a valid instrument for such shock exists. The contemporaneous transmission coefficients are a function of the regression coefficients of the VAR residuals onto the instrument, up to a normalization. Hence, given the instrument, this method ensures that we can isolate the causal effects of a monetary policy shock on the dynamics of our large set of variables without imposing any timing restrictions on the responses. Technical details are discussed in Appendix D.

The crucial step of this identification strategy is, naturally, the choice of the instrument. In Table 2 we summarize a series of tests which we use to guide our choice of the preferred instrument. Conditional on the information set, sampling frequency and time span of the baseline BVAR with 4 lags, we use (*i*) the F statistics of the regression of the policy equation residuals (FEDFUNDS) on the instrument, and (*ii*) a measure of the scalar reliability of the instrument, bounded between zero and 1, as discussed in Mertens and Ravn (2013), together with 90% posterior confidence intervals.[16]

We consider a number of different candidate instruments, all intended to be a noisy measure of the underlying monetary policy shocks. It is important to stress that these are not supposed to be a perfect measure of the shock, nor are they supposed to be perfectly correlated with it. As long as they can be thought of as exogenous with respect to other

[16]When the number of structural shocks of interest is equal to one, the statistical reliability is interpreted as the fraction of the variance in the measured variable (i.e. the instrument) which is explained by the latent shock, or, stated differently, it is the implied squared correlation between the instrument and the latent structural shock (Mertens and Ravn, 2013).

shocks, and to display a non-negligible degree of correlation with the structural shock of interest, then they can in principle be used to identify the shock. Our first candidate is a narrative-based proxy (MPN) constructed extending the narrative shock first proposed in Romer and Romer (2004) up to 2007, following the instructions detailed in Appendix D. The variable captures the changes in the intended federal funds rate that are not taken in response to the Fed's forecasts about either current or future economic developments. Other candidate instruments are instead constructed using market reactions to FOMC announcements, and measured within a tight 30-minute window around the announcements. We use the Target (FOMCF) and Path (PATHF) factors of Gürkaynak et al. (2005), and their underlying components, whose use as instruments for the monetary policy shock was first introduced, at monthly frequency, in Gertler and Karadi (2015).[17] In Table 2, MP1 and FF4 are the monetary surprises implied by changes in the current-month and the three-months-ahead federal funds futures respectively, while ED2, ED3 and ED4 are the surprises in the second, third, and fourth eurodollar futures contracts, which have 1.5, 2.5, and 3.5 quarters to expiration on average. The Target and Path factors are obtained as a rotation of the first two principal components of the surprises in the five contracts above. The rotation is such that the Target factor is interpreted as the surprise changes in the current federal fund rate target, while the Path factor measures changes in the future path of policy which are orthogonal to changes in the current target interest rate (see Gürkaynak et al., 2005). We construct quarterly surprises as the sum of daily data.

We follow Stock et al. (2002) and require the F statistic to be above ten, for the instrument not to be weak. The numbers in Table 2 show that the narrative-based instrument is the only one which is safely above the threshold. All the market-based surprises are well below the critical value, notwithstanding comparable levels of reliability. These numbers confirm the findings of Stock and Watson (2012). It is also worth stressing that the numbers reported relate to the relevance of the instruments, while they remain silent on their exogeneity. Miranda-Agrippino (2016); Miranda-Agrippino and Ricco (2017) discuss the informational content of market-based monetary surprises and show that while

[17] Other applications of high-frequency futures data to the transmission of monetary policy shocks include, among others, Nakamura and Steinsson (2017) and Krishnamurthy and Vissing-Jorgensen (2011).

they successfully capture the component of policy that is unexpected by market participants, they map into the shocks only under the assumption that markets can correctly and immediately disentangle the systematic component of policy from any observable policy action. In the presence of information frictions, the high-frequency surprises are also a function of the information about economic fundamentals that the central bank implicitly discloses at the time of the policy announcements.[18] Failure to account for this effect hinders the correct identification of the shocks, resulting in severe price and real activity puzzles. We confirm this finding also in our quarterly setting. This issue is likely to be mitigated in our framework, due to the large information set included in our VAR. However, we still find that the responses obtained using market-based instruments tend to be more unstable, and hence only report results obtained using high-frequency instruments in the appendix.[19] Hence, we use the narrative-based series as the preferred instrument.

3.2 Discussion of the Results

Figures (6) to (10) collect the responses of our variables of interest to a contractionary US monetary policy shock. These summarize the effects of US monetary policy on the Global Financial Cycle. Figure (5) displays IRFs of a subset of domestic business cycle variables. The full set of responses is in Figure (E.1). The impulse response functions (IRFs) are obtained by estimating a VAR(4).[20] The responses are normalized such that the shock induces a 100bp increase in the effective federal funds rate. We compare responses obtained using the recursive identification scheme (red, solid) to those obtained using the narrative series as an external instrument (blue, dash-dotted). For the recursive identification we plot modal responses to the monetary policy shock together with 68%

[18] The implicit disclosure of information is the Fed information effect in Nakamura and Steinsson (2017), and the signalling channel of monetary policy discussed in Melosi (2017).

[19] In an additional exercise, we use the quarterly MP1 and Target factor (the market-based instruments with the largest F statistic) to identify the shock as follows: (1) calculate the F statistic for each draw of the VAR innovations; (2) retain contemporaneous transmission coefficients associated to F statistics larger than 10; (3) use the median of the retained draws for the responses. IRFs obtained in this way are largely consistent with the ones reported below, and are collected in Figures E.5 and E.6 in Appendix E. However, we note that the number of draws for which the F statistic is larger than 10 is less than 3% of the total: 64 (MP1) and 33 (FOMCF) draws out of 2500.

[20] Using 3 and 5 lags leads to virtually identical responses. See Appendix C for a detailed description of the estimation and priors used.

Table 2: tests for instruments relevance

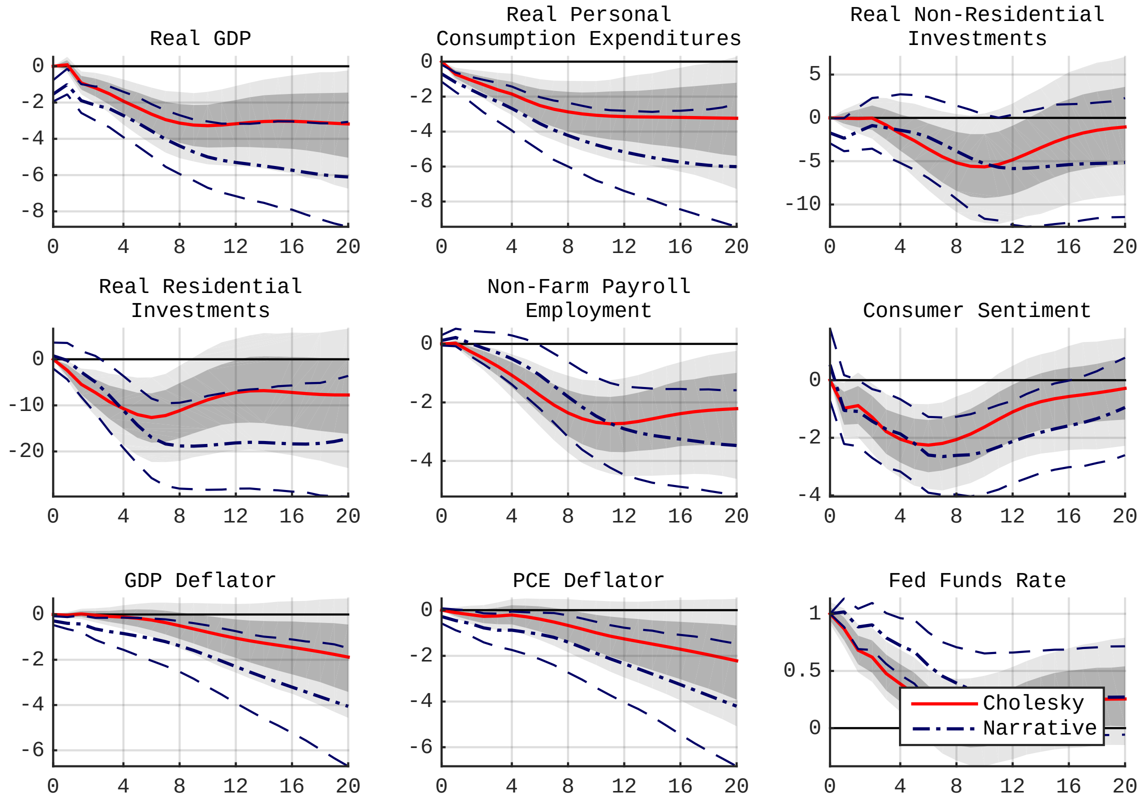
instrument	F stat	90% posterior ci	reliability	90% posterior ci
MPN	16.225	[4.578 21.120]	0.2715	[0.192 0.356]
FOMCF	5.801	[0.669 7.756]	0.2835	[0.195 0.379]
PATHF	0.027	[0.007 2.298]	0.2806	[0.133 0.371]
MP1	4.718	[1.103 8.858]	0.2689	[0.188 0.355]
FF4	4.643	[0.113 5.444]	0.2298	[0.143 0.319]
ED2	3.190	[0.033 3.785]	0.2649	[0.158 0.360]
ED3	1.551	[0.006 2.536]	0.2146	[0.110 0.304]
ED4	1.527	[0.003 1.804]	0.2025	[0.103 0.293]

Note: For each of the candidate instruments the table reports the F statistics associated to the first stage regression of the VAR policy innovation onto the instrument, a measure of statistical reliability, bounded between zero and 1 together with 90% posterior coverage intervals. Candidate instruments are: a narrative-based measure of monetary surprises constructed extending the work of Romer and Romer (2004) up to 2007 and 2009 (first two rows); the Target and Path factors of Gürkaynak et al. (2005), and the surprises in the current-month (MP1) and three-months-ahead (FF4) federal fund futures, and in the second (ED2), third (ED3) and fourth (ED4) eurodollar futures. VAR innovations are from a BVAR(4) on the variables listed in Table 1 from 1980Q1 to 2010Q4.

and 90% posterior coverage bands (grey shaded areas). For the identification with the narrative instrument we report median responses for the retained draws for which the first-stage F statistic is at least equal to 10. Dashed lines are 68% intervals from the distribution of the retained draws. Results are robust to a number of changes in the VAR lag structure, set composition, and length of the sample considered, for which additional charts are reported in Appendix E at the end of the paper.

The responses of US variables to a monetary policy shock and subsequent dynamics are consistent with textbook economic theory, and qualitatively similar under both identification schemes (see also Figure E.1). Output, production and consumption all contract, and so do private residential and non-residential investments, and non farm payroll employment. European GDP increases slightly in response to the US shock, possibly due to an expenditure switching effect, and then contracts with delay. There is no price puzzle: price inflation whether measured by the GDP deflator or the PCE deflator goes down. Consumer sentiment declines. The responses of domestic variables to a contractionary monetary policy shock are thus coherent with the theoretical effects of monetary policy: following an unexpected tightening by the Fed, we witness a contraction of national real

Figure 5: responses of domestic business cycle

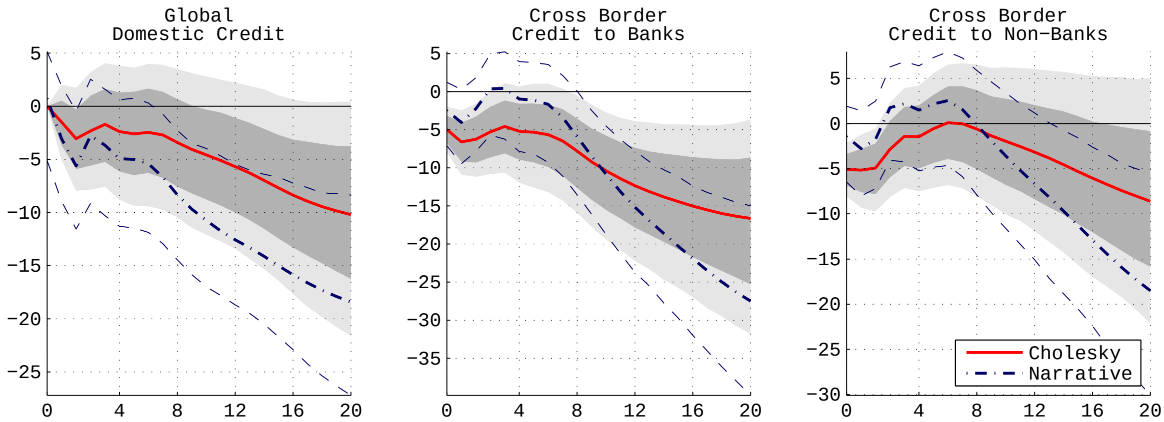


Note: Responses to a US contractionary monetary policy shock that induces a 1% increase in the fed funds rate. [red lines and grey areas] Recursive identification with 68% and 90% posterior coverage bands. [blue lines] Identification with narrative series as external instrument and 68% intervals.

activity and prices. Furthermore, consumption and income decrease as do investment and consumers sentiment. This gives us confidence in the reliability of our identification scheme. We now turn to the main added value of our analysis which is the joint dynamics of global financial variables following a tightening in the centre country of the international monetary system (the US) and zoom on four subsets of those.

First, we look at credit provision both domestically and internationally (Figures 6 and 7). We compute global variables as the cross-sectional sum of country-specific equivalents which are in turn constructed following the instructions detailed in Appendix A. Global inflows are direct cross-border credit flows provided by foreign banks to both banks and non-banks in the recipient country (Avdjiev et al., 2012). Second, we look at banks' leverage (Figure 8). We separate global banks from the aggregate banking sector, due

FIGURE 6: RESPONSES OF GLOBAL CREDIT

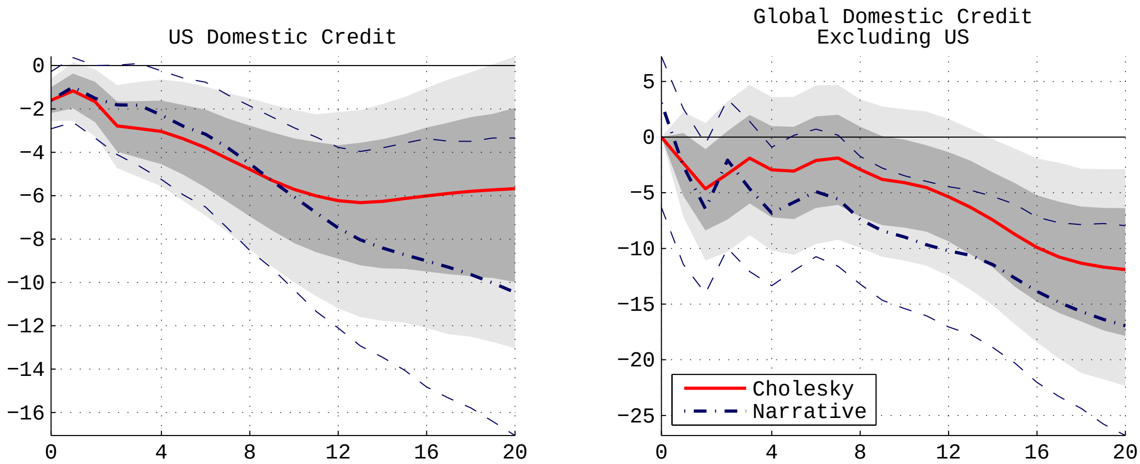


Note: Responses to a US contractionary monetary policy shock that induces a 1% increase in the fed funds rate. [RED LINES AND GREY AREAS] Recursive identification with 68% and 90% posterior coverage bands. [BLUE LINES] Identification with narrative series as external instrument and 68% intervals.

to the fact that global banks that are active in international capital markets manage their leverage in a way that is consistent with the existence of a Value-at-Risk type of constraint. This behaviour distinguishes them from smaller commercial banks. The phenomenon was first highlighted in Adrian and Shin (2010) in the domestic US context. In Section 4.2 we use bank-level data to extend it to an international level. We use data on the leverage of US Security Brokers and Dealers (USBD) and Globally Systemically Important Banks (GSIBs) operating in the Euro Area and the UK. Data on total financial assets and liabilities for USBD are from the Flow of Funds of the Federal Reserve Board, while the aggregate leverage ratios for global banks in the EA and the UK are constructed following the instructions detailed in Appendix A. All those institutions have important capital markets operations. We also provide results using the entire banking sector in the US and the EU, including retail banks, in the Appendix (Figure E.4).[21] Third, we analyze the role played by monetary policy on risk and term premia, and on risk appetite (Figure 9). Here we look at the responses of global asset prices (summarized by the global factor), global risk aversion (calculated as the difference in the responses of the global factor and global market variance along the lines of the decomposition in Section 2), the term spread (calculated as the spread between the 10-year and 1-year constant maturity

[21]Details on the construction of the aggregate banking sector leverage are in Appendix A.

Figure 7: responses of global credit



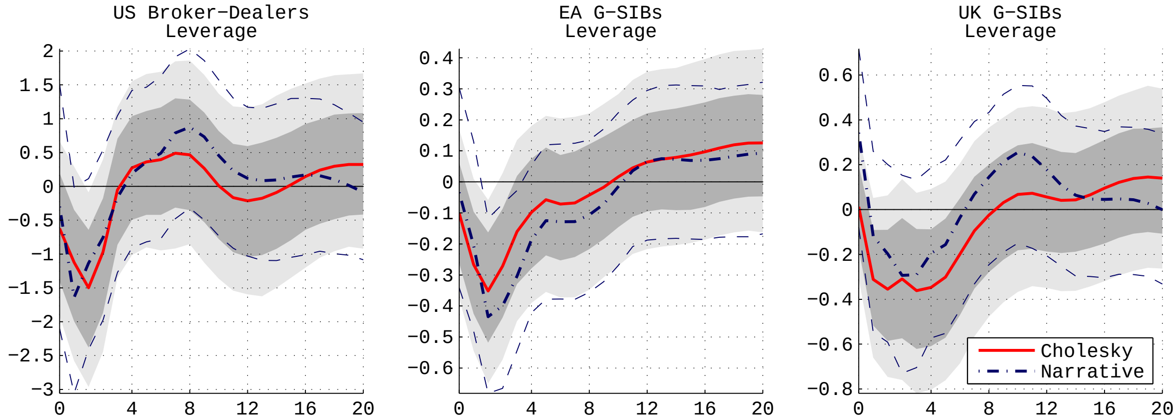
Note: Responses to a US contractionary monetary policy shock that induces a 1% increase in the fed funds rate. [RED LINES AND GREY AREAS] Recursive identification with 68% and 90% posterior coverage bands. [BLUE LINES] Identification with narrative series as external instrument and 68% intervals.

Treasury rates) and the excess bond premium of Gilchrist and Zakrajšek (2012). Lastly, we look at the responses of the US dollar vis-à-vis the Euro and sterling, and at the reaction of the policy rates in both the Euro area and the UK (Figure 10).

The responses of both global domestic and cross-border credit data in Figure 6 highlight how monetary actions in the US influence global financial conditions. Following a monetary tightening, credit provision at the global level contracts significantly. Global inflows, whether directed towards banks or non-banks, contract sharply, and on impact by about 5%. The contraction in cross-border banking flows is stronger and more persistent relative to those directed to non-banks. Domestic credit contracts at a global level. Results on global domestic credit are not driven merely by US data, as is visible in Figure 7, where global domestic credit is split into US and rest of the world components. The decline in credit, both domestic and cross-border, whether we look at flows to banks or to non-banks, is in the order of several percentage points and thus economically significant.

The leverage of global banks also declines significantly (Figure 8). The response is short-lived but substantial. Leverage variables are expressed as the ratio of total financial assets over equities, and enter the VAR in levels, with no transformations. The shock therefore induces a contraction in USBD leverage of 1.5% percentage points within the

Figure 8: responses of leverage of global banks



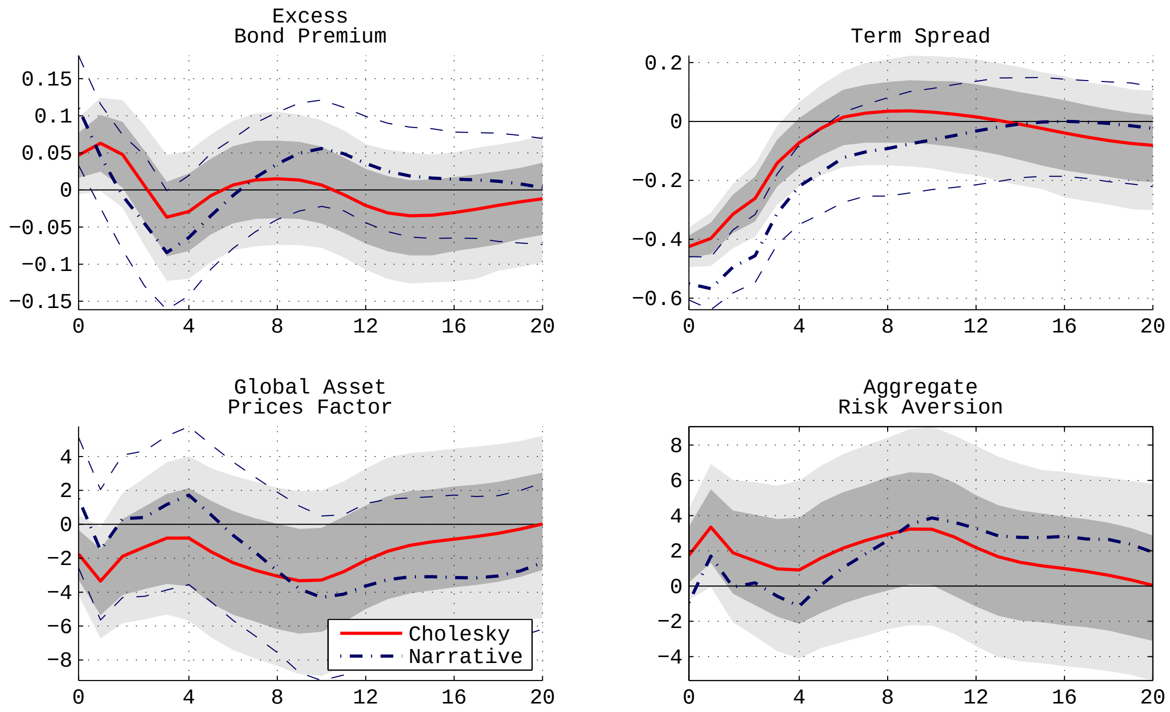
Note: Responses to a US contractionary monetary policy shock that induces a 1% increase in the fed funds rate. [red lines and grey areas] Recursive identification with 68% and 90% posterior coverage bands. [blue lines] Identification with narrative series as external instrument and 68% intervals.

first year. The leverage of European (EA and UK) global banks also contracts, and with similar dynamics. The banking sector as a whole reacts more sluggishly, and in fact registers an initial increase in the median leverage ratio (see Figure E.4 of the Appendix) before contracting. Domestically oriented retail banks take longer to adjust, so that broader banking aggregates only react with a delay to monetary policy shocks, which instead affects more immediately the large banks with important capital market operations. Overall, global banks seem to respond more quickly to changes in the monetary policy stance. This is consistent with these institutions being more reactive to financing conditions when adjusting leverage.

Following a contractionary US monetary policy shock global financial markets also suffer a contraction (Figure 9). The global factor in world risky asset prices declines significantly. Using the decomposition in Section 2 we recover the response of global risk aversion as the difference between the responses of the global factor (inverted) and of global market volatility.[22] Our results point towards a significant impact rise in the aggregate degree of risk aversion in global financial markets following a monetary policy contraction in the centre country. Risk premia also increase on impact, confirming the existence of a financial channel for monetary policy which directly influences borrowing

[22]Posterior coverage bands are obtained by computing the implied response of risk aversion at each draw of the parameters under the recursive identification scheme.

Figure 9: responses of global asset prices



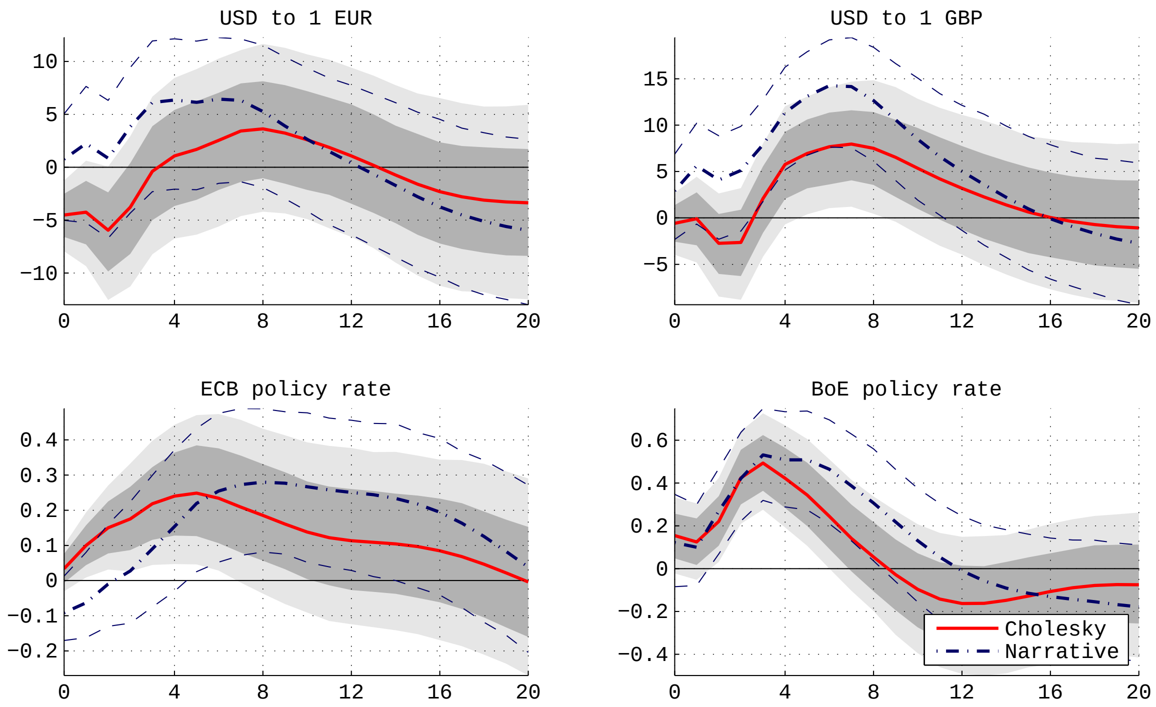
Note: Responses to a US contractionary monetary policy shock that induces a 1% increase in the fed funds rate. [red lines and grey areas] Recursive identification with 68% and 90% posterior coverage bands. [blue lines] Identification with narrative series as external instrument and 68% intervals.

costs. The term spread decreases significantly on impact to rebound in the medium/long horizon. Very interestingly, our analysis therefore shows that the monetary policy of the hegemon influences aggregate risk appetite in international financial markets.

Lastly, Figure 10 reports responses of the exchange rate vis-à-vis the Euro and sterling, and of the UK and Euro Area policy rates. The exchange rate is in both cases measured as US dollars per one unit of the foreign currency, such that a negative reading corresponds to an appreciation of the dollar.[23] The charts in the left panel of Figure 10 collect responses referring to the Euro Area, while the UK equivalents are on the right hand side

[23] For periods preceding the introduction of the Euro, we use the German Mark as the relevant European benchmark currency and convert it using the fixed exchange rate with the Euro chosen at the time of introduction of the common currency. The bilateral exchange rates are about the only two variables for which we are not able to recover impact responses which are robust across identification schemes. Interestingly, however, responses obtained using financial market surprises as external instruments following the instructions in Footnote 19 tend to confirm the initial appreciation of the dollar following a monetary policy contraction.

Figure 10: responses of currency and policy rates



Note: Responses to a US contractionary monetary policy shock that induces a 1% increase in the fed funds rate. [red lines and grey areas] Recursive identification with 68% and 90% posterior coverage bands. [blue lines] Identification with narrative series as external instrument and 68% intervals.

of the figure. The overall qualitative shape of the responses is quite similar in the two countries. There are, however, interesting differences. Following the shock, the dollar appreciates significantly, and on impact, vis-à-vis the Euro. The response is relatively short-lived, and the exchange rate goes back to trend within a year. With respect to sterling, there seems to be no appreciable effect for the first few quarters, following which the dollar depreciates. Notwithstanding the flexibility of the two exchange rates, our results suggest that a contractionary move in the US is likely to be followed by tighter monetary policies both in the UK and the Euro Area. Increases in the policy rates are both positive and significant, and peak to about 50 and 20bp respectively, within the first year after the shock. Interestingly, while the response of the European rate is muted on impact, the UK policy rate jumps on impact by about 20bp. These results are consistent with both a "fear of floating" argument (see Calvo and Reinhart, 2002), and with endogenous developments in the UK and European economies. Hence, even with fully flexible exchange rates, both the Euro Area and the UK respond to the US tightening by raising their domestic policy rates as well. These results are also consistent with the dilemma hypothesis put forward in Rey (2013). With mobile cross-border capital flows, a fully flexible exchange rate is not necessarily enough to fully insulate countries against the spillovers of foreign monetary policy shocks.

While we display results obtained estimating the BVAR using data up to 2010Q4, we verify that our conclusions are not driven by the crisis episode of 2007/2008 by repeating the estimation using data only up to 2007Q2 (Figure E.2). Responses are computed again using both identification schemes discussed above and are virtually identical to the ones presented.[24] This seems to imply that the 2007 financial crisis, while having had unquestionable disruptive effects on the financial markets and having been followed by severe recession episodes worldwide, has not in fact altered the fundamental macroeconomic dynamics and transmission mechanisms both at the national and international levels. A similar conclusion has been reached using national US data by Stock and Watson (2012).

Lastly, we look at the forecast error variance decomposition for a selection of the variables included in the BVAR (Table C.1).[25] We find that US monetary policy explains a non trivial fraction of the forecast error variance of banks' leverage, credit flows and financial markets-related variables. At 1 year horizon, US monetary policy shocks explain about 5% of the forecast error variance for cross border credit flows, and up to 12% at a 4 year horizon. It explains 2 or 3% of the forecast error variance of leverage at the 1 year horizon. We also find that the variance of GDP and inflation explained by the monetary policy shock increases with the horizon. In the long run, monetary policy shocks explain about 3.5% of inflation variance, and 17 % of domestic GDP. Importantly, is also explains over 14% of the variance of global banking flows at the same horizon.

[24]In fact, it is very hard to see the difference between the two sets of IRFs except for the exchange rates: the initial appreciation of the dollar tends to be more precisely estimated in Figure E.2. Results are also robust to ending the sample at the beginning of the zero lower bound period (not reported).

[25]While some of the numbers may seem small at a first glance, it is important to note that the share of explained variance is reduced in rich information VARs, such as ours.

4 Interpretation

4.1 A Simple Model with Heterogeneous Investors

The empirical results show that US monetary policy affects global banks' leverage, credit creation around the world, capital flows, risky asset prices and global risk aversion. We present a stylized model which features investors with heterogeneous risk taking propensities to make sense of the time varying degree of aggregate effective risk aversion. As the relative wealth of investors fluctuates, asset pricing will be determined mostly by one type of investor or the other. Since the 1990s, world asset markets have become increasingly integrated with large cross-border credit, equity and bond portfolio flows. Global banks and asset managers have played an important role in this process of internationalization and account for a large part of these flows. The share of credit in international flows has risen during that period and decreased since 2008 as shown in Figure 4. Bank flows were about 4% of world GDP at the beginning of the year 2000 and they grew to about 30% of world GDP end 2007. During the same period, portfolio debt flows went from about 6% to 15% and portfolio equity flows remained at around 5%. We present an illustrative model of international asset pricing where the risk premium depends on the wealth distribution between leveraged global banks on the one hand, and asset managers, such as insurance companies or sovereign wealth funds, on the other. The model presented in this section is stylized and only here to help us interpret the data.[26]

The model builds directly on the work of Zigrand et al. (2010) and Adrian and Shin (2014).[27] We consider a world in which there are two types of investors: global banks and asset managers. Global banks are leveraged entities that fund themselves in dollars for their operations in global capital markets. They can borrow at the US risk-free rate and lever to buy a portfolio of world risky securities, whose returns are in dollars. They are risk-neutral investors and subject to a Value-at-Risk (VaR) constraint, which is imposed on them by regulation.[28] We present microeconomic evidence pertaining to the leverage

[26]For a more realistic dynamic stochastic general equilibrium model of asset pricing with heterogeneous investors and monetary policy see Coimbra and Rey (2017). Other types of model which generate time varying risk aversion are for example models with consumption habit (see Campbell and Cochrane (1999))

[27]See also Etula (2013).

[28]Their risk neutrality is an assumption which may be justified by the fact that they benefit from an implicit bailout guarantee, either because they are universal banks, and are therefore part of a deposit

and risk taking behaviour of banks in Section 4.2.

The second type of investors are asset managers who, like global banks, acquire risky securities in world markets and can borrow at the US risk-free rate. Asset managers also hold a portfolio of regional assets (for example regional real estate) which is not traded in financial markets, perhaps because of information asymmetries. Asset managers are standard mean-variance investors and exhibit a positive degree of risk aversion that limits their desire to leverage.[29]

Global Banks

Global banks maximize the expected return of their portfolio of world risky assets subject to a Value-at-Risk constraint.[30] The VaR imposes an upper limit on the amount a bank is predicted to lose on a portfolio with a certain probability. We denote by $\mathbf{R}_t$ the vector of excess returns in dollars of all traded risky assets in the world. We denote by $\mathbf{x}_t^B$ the portfolio shares of a global bank. We call w_t^B the equity of the bank. The maximization problem of a global bank is

$$\max_{\mathbf{x}_t^B} \mathbb{E}_t \left(\mathbf{x}_t^{B\prime} \mathbf{R}_{t+1} \right)$$
$$\text{subject to } VaR_t \leq w_t^B,$$

with the VaR_t defined as a multiple α of the standard deviation of the bank portfolio $VaR_t = \alpha w_t^B \left[\mathbb{V}ar_t \left(\mathbf{x}_t^{B\prime} \mathbf{R}_{t+1} \right) \right]^{\frac{1}{2}}$

Taking the first order condition and using the fact that the constraint is binding (since banks are risk neutral) gives the following solution for the vector of asset demands:

$$\mathbf{x}_t^B = \frac{1}{\alpha \lambda_t} \left[\mathbb{V}ar_t(\mathbf{R}_{t+1}) \right]^{-1} \mathbb{E}_t(\mathbf{R}_{t+1}). \tag{1}$$

guarantee scheme, or because they are too big to fail. Whatever the microfoundations, the crisis has provided ample evidence that global banks have taken on large amounts of risk and levered massively.

[29]The fact that only asset managers, and not the global banks, have a regional portfolio is non essential; global banks could be allowed to hold a portfolio of regional loans or assets as well. The asymmetry in risk aversion (risk neutral banks with VaR constraint and risk averse asset managers), however, is important for the results.

[30]VaR constraints have been used internally for the risk management of large banks for a long time and have entered the regulatory sphere with Basel II and III. For a microfoundation of VaR constraints, see Adrian and Shin (2014).

This is formally similar to the portfolio allocation of a mean variance investor. In Eq. (1), λ_t is the Lagrange multiplier: the VaR constraint plays the same role as risk aversion.[31]

Asset Managers

Asset managers are standard mean-variance investors with degree of risk aversion σ. They have access to the same set of traded assets as global banks. We call $\mathbf{x}_t^I$ the vector of portfolio weights of the asset managers in tradable risky assets. Asset managers also invest in local (regional) non traded assets. We denote by $\mathbf{y}_t^I$ the fraction of their wealth invested in those regional assets. The vector of excess returns on these non tradable investments is $\mathbf{R}_t^N$. Finally, we call w_t^I the equity of asset managers. An asset manager chooses his portfolio of risky assets by maximizing

$$\max_{x_t^I} \mathbb{E}_t \left(\mathbf{x}_t^{I\prime} \mathbf{R}_{t+1} + \mathbf{y}_t^{I\prime} \mathbf{R}_{t+1}^N \right) - \frac{\sigma}{2} \mathbb{V}ar_t \left(\mathbf{x}_t^{I\prime} \mathbf{R}_{t+1} + \mathbf{y}_t^{I\prime} \mathbf{R}_{t+1}^N \right).$$

The optimal portfolio choice in risky tradable securities for an asset manager will be

$$\mathbf{x}_t^I = \frac{1}{\sigma} \left[\mathbb{V}ar_t(\mathbf{R}_{t+1}) \right]^{-1} \left[\mathbb{E}_t(\mathbf{R}_{t+1}) - \sigma \mathbb{C}ov_t(\mathbf{R}_{t+1}, \mathbf{R}_{t+1}^N) \mathbf{y}_t^I \right]. \tag{2}$$

Market clearing conditions

The market clearing condition for risky traded securities is $\mathbf{x}_t^B \frac{w_t^B}{w_t^B + w_t^I} + \mathbf{x}_t^I \frac{w_t^I}{w_t^B + w_t^I} = \mathbf{s}_t$ where $\mathbf{s}_t$ is a world vector of net asset supplies for traded assets.

Proposition 1 (Risky Asset Returns) *Using Eq. (1) and (2) and the market clearing conditions, the expected excess returns on tradable risky assets can be rewritten as the sum of a global component (aggregate variance scaled by aggregate effective risk aversion) and a regional component:*

$$\mathbb{E}_t \left(\mathbf{R}_{t+1} \right) = \Gamma_t \mathbb{V}ar_t(\mathbf{R}_{t+1}) \ \mathbf{s}_t + \Gamma_t \mathbb{C}ov_t(\mathbf{R}_{t+1}, \mathbf{R}_{t+1}^N) \mathbf{y}_t, \tag{3}$$

where $\Gamma_t \equiv \left[\frac{w_t^B}{\alpha \lambda_t} + \frac{w_t^I}{\sigma} \right]^{-1} \left(w_t^B + w_t^I \right)$.

[31] It is possible to solve out for the Lagrange multiplier using the binding VaR constraint (see Zigrand et al., 2010). We find $\lambda_t = \left[\mathbb{E}_t(\mathbf{R}_{t+1})' \left[\mathbb{V}ar_t(\mathbf{R}_{t+1}) \right]^{-1} \mathbb{E}_t(\mathbf{R}_{t+1}) \right]^{-1/2}$.

Γ_t is the wealth-weighted average of the "risk aversions" of asset managers and of the global banks. It can thus be interpreted as the aggregate degree of effective risk aversion of the market. If all the wealth were in the hands of asset managers, for example, aggregate risk aversion would be equal to σ. The empirical counterpart of Eq. (3) is the decomposition of risky asset returns into a global component (also a function of the aggregate degree of risk aversion) and a regional component shown in Section 2. One possible interpretation of the decline in aggregate effective risk aversion observed between 2003 and 2007 in Figure 3 is therefore that as global banks become large, they are more important for the pricing of risky assets, and aggregate risk aversion goes down. This trend is reversed after the crisis, when instead asset managers become relatively bigger.

Proposition 2 (Global Banks Returns) *The expected excess return of a global bank portfolio in our economy is given by*

$$\begin{aligned} \mathbb{E}_t(\mathbf{x}_t^{B\prime}\mathbf{R}_{t+1}) &= \Gamma_t \mathbb{C}ov_t(\mathbf{x}_t^{B\prime}\mathbf{R}_{t+1}, \mathbf{s}_t^{\prime}\mathbf{R}_{t+1}) + \Gamma_t \mathbb{C}ov_t(\mathbf{x}_t^{B\prime}\mathbf{R}_{t+1}, \mathbf{y}_t^{\prime}\mathbf{R}_{t+1}^N) \\ &= \beta_t^{BW}\Gamma_t + \Gamma_t \mathbb{C}ov_t(\mathbf{x}_t^{B\prime}\mathbf{R}_{t+1}, \mathbf{y}_t^{\prime}\mathbf{R}_{t+1}^N), \end{aligned} \tag{4}$$

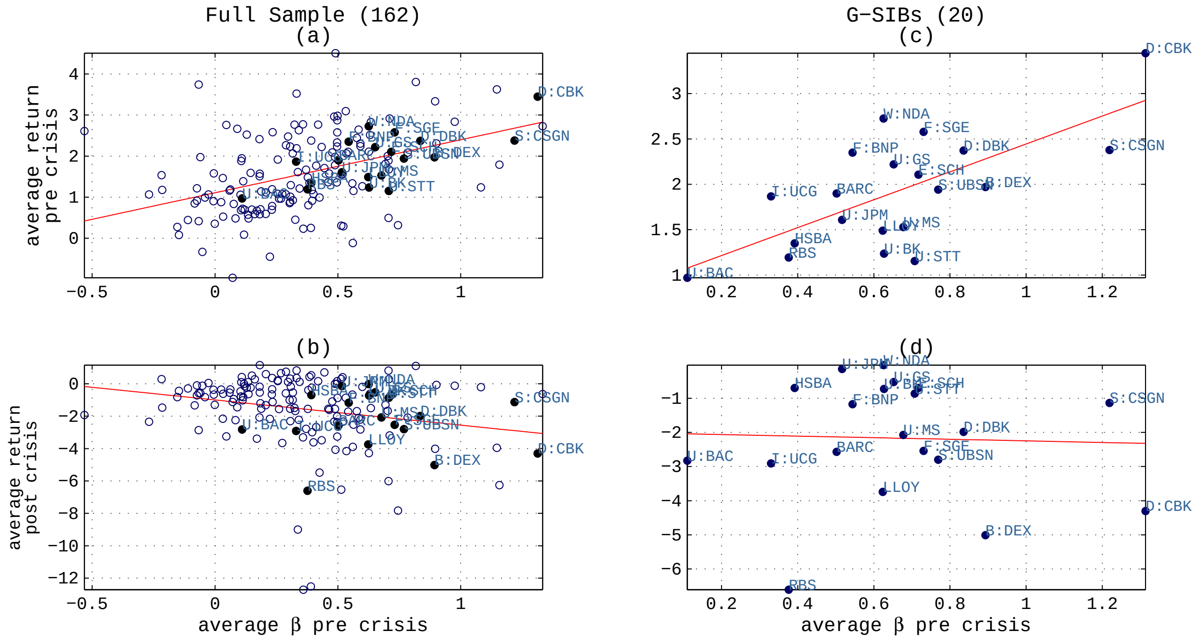
where β_t^{BW} is the beta of a global bank with the world market.

The more correlated a global bank portfolio with the world portfolio, the higher the expected asset return, *ceteris paribus*. The high-β_t^{BW} global banks are the ones loading more on world risk. The excess return is scaled up by the global degree of risk aversion in the economy – Γ_t.

4.2 Evidence on Global Banks

Using US data on quarterly growth rates of both total assets and leverage (defined as total assets over equity, measured at book value), Adrian and Shin (2010) show that the positive association between leverage and size of balance sheets (in growth rate) is a particular feature of broker-dealers, which distinguishes them from retail banks and from households. Using balance sheet data for the same international sample of financial institutions we used in Section 3, we show in Figure A.3 that the positive association between leverage and size of assets goes well beyond the US borders. We calculate leverage along

Figure 11: Correlation between banks' returns and loading on the global factor



Note: In each subplot, the x axis reports the average β^{BW} in the three years preceding the onset of the financial crisis (August 2007), while the y axis records average returns in percentage points. Filled blue circles highlight GSIBs within the broader population of banks (hollow circles); the sign of the correlation is visualized by a red regression line in each plot. Panels (a) and (b): banks average returns pre (2003-2007) and post (2007-2010) crisis as a function of their pre-crisis betas. Panels (c) and (d) GSIBs subsample. *Source:* Datastream, authors calculations.

the lines of Kalemli-Ozcan et al. (2012).[32] Figure A.3 shows the correlation between quarterly asset growth and quarterly leverage growth for four different categories of international financial institutions included in our sample. The procyclicality of leverage is more evident the more the points align with the 45 degrees lines (in red) and is more a feature of the behaviour of financial institutions which engage in global capital markets operations, a subset which included in particular the former stand-alone investment banks. The same holds true for the large European (UK, Euro Area and Switzerland) universal banks, whose investment departments have played a central role in channelling US Dollar liquidity worldwide in the years immediately preceding the financial crisis (see Shin, 2012). Many of those large European Banks are GSIBs (see Table A.4).

[32]We use a panel 166 financial institutions in 20 countries from 2000 to 2010. We identify a subset of 21 large banks who have been classified as Globally Systemically Important Banks (GSIBs). A complete list of institutions included in our set is in Table A.4.

Figure 11 is the empirical counterpart of Eq. (4). It reports the correlation between the returns of each bank and their loadings β_t^{BW} on the global risk factor of Section 2, calculated over the entire population of banks – panels (a) and (b) –, and the GSIBs subsample – panels (c) and (d) – respectively. We use August 2007 as a break point to distinguish between pre and post crisis periods. Results indicate, as expected, a positive correlation between loading up on systemic risk before the crisis and getting high returns. Panels (a) and (c) show that, relative to the larger population, GSIBs tend to have both higher average betas and larger returns. This suggests that global banks were systematically loading more on world risk in the run-up to the financial crisis, and that their behaviour was delivering larger average returns, compared to the average bank in our sample. The higher loadings on risk are consistent with the build-up of leverage in the years prior to the crisis documented in Figure A.2. Furthermore, panels (b) and (d) sort the banks on the x-axis according to their pre-crisis betas, but report their post crisis returns on the y axis. The charts show how the institutions that were loading more on global risk pre crisis suffered the largest losses after the systemic meltdown. The micro data on global banks are therefore consistent with US monetary policy being transmitted internationally through the financial system.

5 Conclusions

This paper establishes the importance of US monetary policy as one of the drivers of the Global Financial Cycle. The hegemon monetary policy influences global risk appetite. First, we show that one global factor explains an important part of the variance of a large cross section of returns of risky asset prices around the world. This factor can be interpreted as reflecting movements in aggregate volatility on world equity markets, and time-varying market-wide risk aversion. We find in particular evidence of a significant decline in effective risk aversion between 2003 and the beginning of 2007, that is during the crisis build up phase. That period matches the increased importance of global banks in international capital markets. Second, we investigate the links of the Global Financial Cycle with US monetary policy, as the dollar is an important funding currency for global intermediaries, and a large portion of portfolios worldwide are denominated in dollars.[33] Because we use a medium-scale Bayesian VAR and a robust identification method, we believe we are the first paper able to look meaningfully at the joint behaviour of the domestic business cycle and international financial variables in a single comprehensive modelling framework. Responses to a monetary policy shock in the US are identified using a standard recursive scheme, and a narrative measure of monetary policy disturbances à la Romer and Romer (2004) as an external instrument.

We find evidence of powerful monetary policy spillovers from the US to the rest of the world. When the US Federal Reserve tightens, domestic output, investment, and inflation contract. But, importantly, we also see significant movements in international financial variables: the global factor in asset prices goes down, spreads go up, global domestic and cross-border credit go down significantly and leverage decreases, first among US broker-dealers and for global banks in the Euro area and the UK, then among the broader banking sector in the US and in Europe. We also find evidence of an endogenous reactions of monetary policy rates in the UK and in the Euro area. Hence, we find that US monetary policy is a driver of the Global Financial Cycle.[34] This is an important result as it challenges the degree of monetary policy independence enjoyed by countries around the world, even those who have flexible exchange rates such as the UK or the Euro Area. This fits with the claim of Rey (2013) that the Mundellian trilemma may have really morphed into a dilemma: as long as capital flows across borders are free and macro prudential tools are not used to control credit growth, monetary conditions in any country, even one with a flexible exchange rate, are partly dictated by the monetary policy of the centre country (the US). In other words, exchange rate movements cannot insulate a country from US monetary policy shocks, and a flexible exchange rate country cannot run a fully independent monetary policy. This of course does not mean that exchange rate regimes do not matter, as Klein and Shambaugh (2013) and Obstfeld (2015) rightly point out.[35] This international transmission mechanism of monetary policy is *a priori*

[33]For recent discussions of the international reserve currency role of the dollar see Farhi and Maggiori (2017). Gopinath (2016) analyzes the disproportionate role of the dollar in trade invoicing, and Gopinath and Stein (2017) the synergies between some of those roles.

[34]We note that our results do not depend on the inclusion of the crisis in our sample, suggesting that the fundamental dynamics of macroeconomic variables and the transmission channels of monetary policy have not been noticeably altered by the financial collapse of 2007-8.

[35]For interesting theoretical modelling of the challenges of the trilemma in a standard neo-Keynesian

consistent with models where financial market imperfections play a role via Value-at-Risk limits, or models with net worth or equity constraints, all of which have been developed or revived recently.

It still remains to be seen though whether open economy extensions of these models would be able to generate a Global Financial Cycle whose features would match closely the empirical regularities uncovered in this paper.[36] Understanding more finely the international transmission channels of monetary policy is, in our view, a key challenge for Central Bankers and academics alike. It is hard to see at this point how the Global Financial Cycle and the Mundellian trilemma can fully coexist.

model, see Farhi and Werning, 2012, 2013).

[36]For a more detailed discussion of the theoretical challenges when modelling international monetary policy transmission channels, see Bernanke (2017) and Rey (2016).

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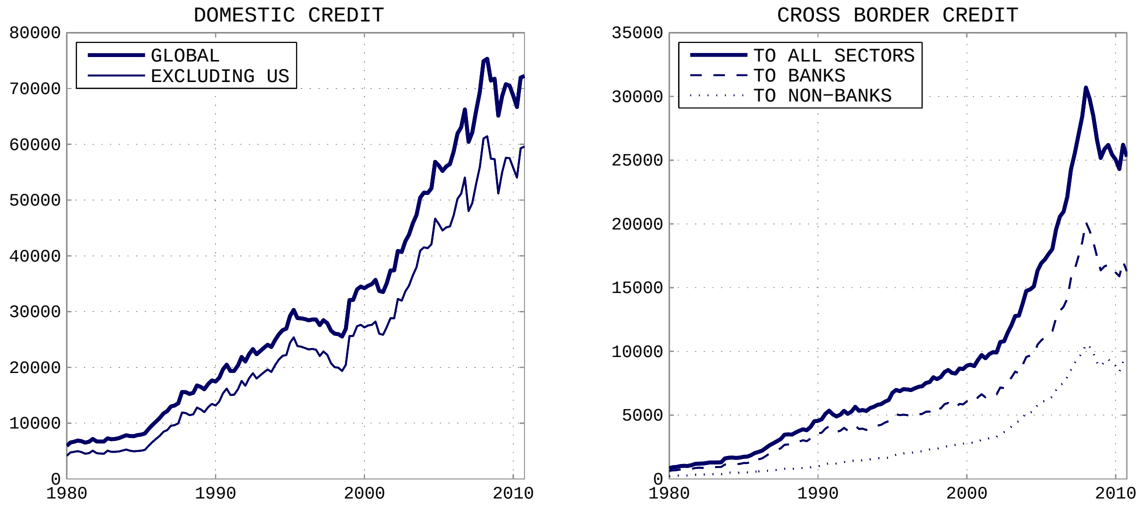
A Credit and Banking Data – For Online Publication

A.1 Domestic and Cross-Border Credit

Credit data, both domestic and cross-border, are constructed using data collected and distributed by the IMF's International Financial Statistics (IFS) and the Bank for International Settlements (BIS) databases respectively, for the countries listed in table A.1.

FIGURE A.1: GLOBAL CREDIT



Note: Global Domestic Credit and Global Cross-Border Inflows constructed as the cross sectional sum of country-specific credit variables. The unit in both plots is Billion USD.

Following Gourinchas and Obstfeld (2012) we construct National Domestic Credit for each country as the difference between Domestic Claims to All Sectors and Net Claims to Central Government reported by each country's financial institutions; however, we only consider claims of depository corporations excluding central banks. Specifically, we refer to the Other Depository Corporation Survey available within the 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. This classification was adopted starting from 2001, prior to that date we refer to the Deposit Money Banks Survey. Raw data are quarterly and expressed in national currency, we convert them in Billion USD equivalents using end of period exchange rates again available within the IFS. Whenever there exists a discontinuity between data available under the old and new classifications we interpolate the missing observations. Global

Table A.1: List of Countries Included

North America	Latin America	Central and Eastern Europe	Western Europe	Emerging Asia	Asia Pacific	Africa and Middle East
Canada	Argentina	Belarus	Austria	China	Australia	Israel
US	Bolivia	Bulgaria	Belgium	Indonesia	Japan	South Africa
	Brazil	Croatia	Cyprus	Malaysia	Korea	
	Chile	Czech Republic	Denmark	Singapore	New Zealand	
	Colombia	Hungary	Finland	Thailand		
	Costa Rica	Latvia	France			
	Ecuador	Lithuania	Germany			
	Mexico	Poland	Greece*			
		Romania	Iceland			
		Russian Federation	Ireland			
		Slovak Republic	Italy			
		Slovenia	Luxembourg			
		Turkey	Malta			
			Netherlands			
			Norway			
			Portugal			
			Spain			
			Sweden			
			Switzerland			
			UK			

Note: Countries included in the construction of the Domestic Credit and Cross-Border Credit variables used throughout the paper. Greece is not included in the computation of Global Domestic Credit due to poor quality of original national data.

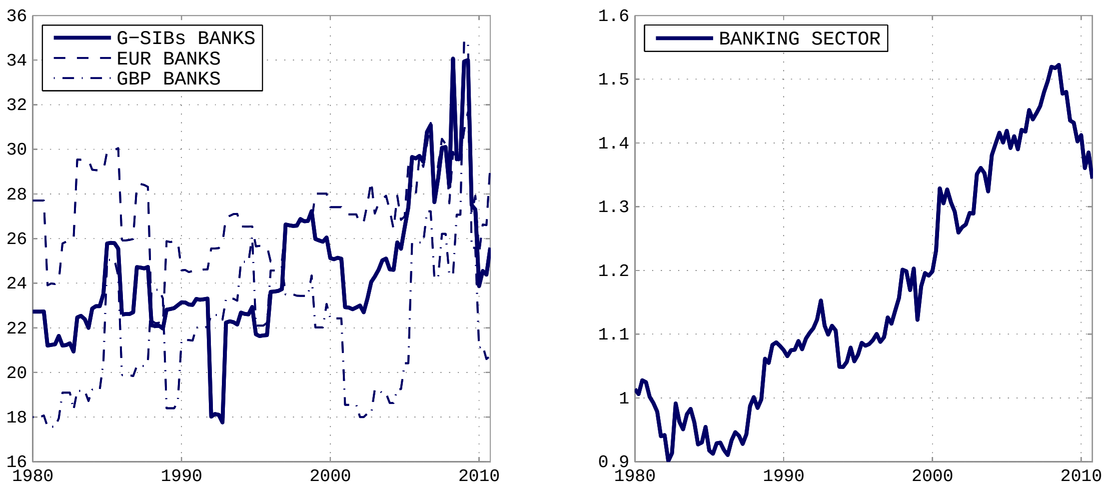
Domestic Credit is finally constructed as the cross-sectional sum of the National Domestic Credit variables.

To construct the Cross-Border Capital Inflows measures used within the paper we adopt the definition of Direct Cross-Border Credit in Avdjiev et al. (2012). We use original data available at the BIS Locational Banking Statistics Database and collected under External Positions of Reporting Banks vis-à-vis Individual Countries (Table 6). Data refer to the outstanding amount of Claims to All Sectors and Claims to Non-Bank Sector in all currencies, all instruments, declared by all BIS reporting countries with counterparty location being the individual countries in Table A.1. We then construct Claims to the Banking Sector as the difference between the two categories available. Original data are available at quarterly frequency in Million USD. Global Inflows are finally calculated as the cross-sectional sum of the national variables. Global domestic credit and global cross-border capital inflows are plotted in Figure A.1.

A.2 Banking Sector and Individual Banks Leverage data

To construct an aggregate country-level measure of banking sector leverage we follow Forbes (2012) and build it as the ratio between Claims on Private Sector and Transferable plus Other Deposits included in Broad Money of depository corporations excluding central banks. Original data are in national currencies and are taken from the Other Depository Corporations Survey; Monetary Statistics, International Financial Statistics database. The classification of deposits within the former Deposit Money Banks Survey corresponds to Demand, Time, Savings and Foreign Currency Deposits. Using these national data as a reference, we construct the European Banking Sector Leverage variable as the median leverage ratio among Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain and United Kingdom.

Figure A.2: European Banks Leverage



Note: [LEFT PANEL] Leverage ratio calculated for the European GSIBs with a detail on EUR and GBP banks using the institutions and classification in Table A.2. [RIGHT PANEL] Aggregated European banking sector leverage ratio measured as the median of European countries banking sector leverage variables following Forbes (2012).

The aggregate Leverage Ratios (defined as Total Assets over Equity) for the Global Systemic Important Banks in the Euro-Area and United-Kingdom used in the BVAR are constructed as weighted averages of individual banks data. Balance sheet Total Assets (DWTA) and Shareholders' Equity (DWSE) are from the Thomson Reuter Worldscope

Table A.2: European G-SIBs.

NAME	ISIN	GICS INDUSTRY	COUNTRY	EA LEV	UK LEV
BNP Paribas	FR0000131104	Commercial Banks	France	•	
Credit Agricole	FR0000045072	Commercial Banks	France	•	
Societe Generale	FR0000130809	Commercial Banks	France	•	
Commerzbank	DE0008032004	Commercial Banks	Germany	•	
Deutsche Bank	DE0005140008	Capital Markets	Germany	•	
Unicredit	IT0004781412	Commercial Banks	Italy	•	
ING Bank	NL0000113892	Commercial Banks	Netherlands	•	
BBVA	ES0113211835	Commercial Banks	Spain	•	
Banco Santander	ES0113900J37	Commercial Banks	Spain	•	
Nordea Group	SE0000427361	Commercial Banks	Sweden		
Credit Suisse Group	CH0012138530	Capital Markets	Switzerland		
UBS	CH0024899483	Capital Markets	Switzerland		
Royal Bank of Scotland	GB00B7T77214	Commercial Banks	UK		•
Barclays	GB0031348658	Commercial Banks	UK		•
HSBC Holdings	GB0005405286	Commercial Banks	UK		•
Lloyds Banking Group	GB0008706128	Commercial Banks	UK		•
Standard Chartered	GB0004082847	Diversified Fin'l	UK		•

Note: European Global Systemically Important Banks included in the construction of GSIBs Leverage Ratios; the last two columns highlight the components of EUR and GDP Leverage respectively.

Datastream database and available at quarterly frequency. Weights are proportional to Market Capitalisation (WC08001) downloaded from the same source. Details on the banks included and their characteristics are summarised in Table A.2 below. The aggregated banking sector leverage and the leverage ratio of the European GSIBs are plotted in Figure A.2.

Figures 11 and A.3 are built using data on individual banks total return indices excluding dividends taken from Thomson Reuters Worldscope database at quarterly frequency. Data are collected directly from banks balance sheets and Leverage Ratios are computed as the ratio between Total Assets (DWTA) and Common/Shareholders' Equity (DWSE). Total Assets include cash and due from banks, total investments, net loans, customer liability on acceptances (if included in total assets), investment in unconsolidated subsidiaries, real estate assets, net property, plant and equipment, and other assets. Descriptive statistics for bank level data and a complete list of the institutions included in the sample are provided in Tables A.3 and A.4 respectively. Although the data source is different, the calculation follows Kalemli-Ozcan et al. (2012).

Table A.3: Bank Data Summary Statistics.

(a)

	All (155)			GSIBs (25)			CommB (123)		
	A	E	L	A	E	L	A	E	L
min	0.3	0.0	1.113	60.9	2.7	6.353	0.4	0.0	4.887
max	3880.6	219.8	327.2	3880.6	219.8	163.5	3880.6	219.8	327.2
mean	251.7	12.9	18.73	1121.2	53.4	24.59	258.4	13.5	19.86
median	54.8	3.9	15.92	1108.3	39.1	22.76	55.0	3.6	17

(b)

	CapM (18)			T&MF (5)			Other Fin'l(9)		
	A	E	L	A	E	L	A	E	L
min	0.3	0.2	1.113	1.9	0.1	2.989	5.5	0.6	2.242
max	3595.1	76.9	136.2	61.2	5.7	19.5	310.0	42.8	65.13
mean	364.5	15.4	16.06	21.7	2.5	9.933	63.1	6.7	13.65
median	90.2	7.3	12.98	21.7	1.3	7.978	26.9	3.3	7.259

Note: Summary statistics for bank-level data used in the analysis. (A) Total Assets, (E) Shareholders' Equity, (L) Leverage Ratio. [panel (a)] full sample (All), Global Systemically Important Banks (GSIBs), Commercial Banks (CommB). [panel (b)] Capital Markets (CapM), Thrifts & Mortgage Finance (T&MF), Other Financial (Other Fin'l, includes Diversified Financial Services and Consumer Finance). Total assets and common equity are in Billion USD. Numbers in parentheses denote the number of banks in each category.

Table A.4: List of Financial Institutions included

ISIN Code	Bank Name	Geo Code	Country	GICS Industry	G-SIB
AT0000606306	RAIFFEISEN BANK INTL.	EU	Austria	Commercial Banks	
AT0000625108	OBERBANK	EU	Austria	Commercial Banks	
AT0000652011	ERSTE GROUP BANK	EU	Austria	Commercial Banks	
BE0003565737	KBC GROUP	EU	Belgium	Commercial Banks	
GB0005405286	HSBC HOLDING	EU	Great Britain	Commercial Banks	•
GB0008706128	LLOYDS BANKING GROUP	EU	Great Britain	Commercial Banks	•
GB0031348658	BARCLAYS	EU	Great Britain	Commercial Banks	•
GB00B7T77214	ROYAL BANK OF SCTL.GP.	EU	Great Britain	Commercial Banks	•
DK0010274414	DANSKE BANK	EU	Denmark	Commercial Banks	
DK0010307958	JYSKE BANK	EU	Denmark	Commercial Banks	
FR0000045072	CREDIT AGRICOLE	EU	France	Commercial Banks	•
FR0000031684	PARIS ORLEANS	EU	France	Capital Markets	
FR0000120685	NATIXIS	EU	France	Commercial Banks	
FR0000130809	SOCIETE GENERALE	EU	France	Commercial Banks	•
FR0000131104	BNP PARIBAS	EU	France	Commercial Banks	•
DE0008001009	DEUTSCHE POSTBANK	EU	Germany	Commercial Banks	
DE0005140008	DEUTSCHE BANK	EU	Germany	Capital Markets	•

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Table A.4 – continued from previous page

ISIN Code	Bank Name	Geo Code	Country	GICS Industry	G-SIB
DE000CBK1001	COMMERZBANK	EU	Germany	Commercial Banks	•
IE0000197834	ALLIED IRISH BANKS	EU	Ireland	Commercial Banks	
IE0030606259	BANK OF IRELAND	EU	Ireland	Commercial Banks	
IE00B59NXW72	PERMANENT TSB GHG.	EU	Ireland	Commercial Banks	
IT0005002883	BANCO POPOLARE	EU	Italy	Commercial Banks	
IT0003487029	UNIONE DI BANCHE ITALIAN	EU	Italy	Commercial Banks	
IT0000062957	MEDIOBANCA BC.FIN	EU	Italy	Capital Markets	
IT0000064482	BANCA POPOLARE DI MILANO	EU	Italy	Commercial Banks	
IT0000072618	INTESA SANPAOLO	EU	Italy	Commercial Banks	
IT0001005070	BANCO DI SARDEGNA RSP	EU	Italy	Commercial Banks	
IT0004984842	BANCA MONTE DEI PASCHI	EU	Italy	Commercial Banks	
IT0004781412	UNICREDIT	EU	Italy	Commercial Banks	•
NO0006000801	SPAREBANK 1 NORD-NORGE	EU	Norway	Commercial Banks	
NO0006000900	SPAREBANKEN VEST	EU	Norway	Commercial Banks	
PTBCP0AM0007	BANCO COMR.PORTUGUES R	EU	Portugal	Commercial Banks	
PTBES0AM0007	BANCO ESPIRITO SANTO	EU	Portugal	Commercial Banks	
PTBPI0AM0004	BANCO BPI	EU	Portugal	Commercial Banks	
ES0113860A34	BANCO DE SABADELL	EU	Spain	Commercial Banks	
ES0113211835	BBV.ARGENTARIA	EU	Spain	Commercial Banks	•
ES0113679I37	BANKINTER R	EU	Spain	Commercial Banks	
ES0113790226	BANCO POPULAR ESPANOL	EU	Spain	Commercial Banks	
ES0113900J37	BANCO SANTANDER	EU	Spain	Commercial Banks	•
SE0000148884	SEB A	EU	Sweden	Commercial Banks	
SE0000193120	SVENSKA HANDBKN.A	EU	Sweden	Commercial Banks	
SE0000242455	SWEDBANK A	EU	Sweden	Commercial Banks	
SE0000427361	NORDEA BANK	EU	Sweden	Commercial Banks	•
CH0012138530	CREDIT SUISSE GROUP N	EU	Switzerland	Capital Markets	•
CH0012335540	VONTOBEL HOLDING	EU	Switzerland	Capital Markets	
CH0018116472	BANK COOP	EU	Switzerland	Commercial Banks	
CH0024899483	UBS R	EU	Switzerland	Capital Markets	•
CA0636711016	BANK OF MONTREAL	AM	Canada	Commercial Banks	
CA0641491075	BK.OF NOVA SCOTIA	AM	Canada	Commercial Banks	
CA1360691010	CANADIAN IMP.BK.COM.	AM	Canada	Commercial Banks	
CA13677F1018	CANADIAN WESTERN BANK	AM	Canada	Commercial Banks	
CA51925D1069	LAURENTIAN BK.OF CANADA	AM	Canada	Commercial Banks	
CA6330671034	NAT.BK.OF CANADA	AM	Canada	Commercial Banks	
CA7800871021	ROYAL BANK OF CANADA	AM	Canada	Commercial Banks	
CA8911605092	TORONTO-DOMINION BANK	AM	Canada	Commercial Banks	
US0258161092	AMERICAN EXPRESS	AM	United States	Diversified Fin'l	
US0454871056	ASSOCIATED BANC-CORP	AM	United States	Commercial Banks	
US0462651045	ASTORIA FINL.	AM	United States	Thrifts & Mortgage	
US0549371070	BB&T	AM	United States	Commercial Banks	
US05561Q2012	BOK FINL.	AM	United States	Commercial Banks	
US0596921033	BANCORPSOUTH	AM	United States	Commercial Banks	
US0605051046	BANK OF AMERICA	AM	United States	Commercial Banks	•
US0625401098	BANK OF HAWAII	AM	United States	Commercial Banks	
US0640581007	BANK OF NEW YORK MELLON	AM	United States	Capital Markets	•
US14040H1059	CAPITAL ONE FINL.	AM	United States	Diversified Fin'l	
US1491501045	CATHAY GEN.BANCORP	AM	United States	Commercial Banks	
US1729674242	CITIGROUP	AM	United States	Commercial Banks	•
US1785661059	CITY NATIONAL	AM	United States	Commercial Banks	
US2003401070	COMERICA	AM	United States	Commercial Banks	
US2005251036	COMMERCE BCSH.	AM	United States	Commercial Banks	
US2298991090	CULLEN FO.BANKERS	AM	United States	Commercial Banks	

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Table A.4 – continued from previous page

ISIN Code	Bank Name	Geo Code	Country	GICS Industry	G-SIB
US2692464017	E*TRADE FINANCIAL	AM	United States	Capital Markets	
US27579R1041	EAST WEST BANCORP	AM	United States	Commercial Banks	
US3167731005	FIFTH THIRD BANCORP	AM	United States	Commercial Banks	
US31946M1036	FIRST CTZN.BCSH.A	AM	United States	Commercial Banks	
US3205171057	FIRST HORIZON NATIONAL	AM	United States	Commercial Banks	
US33582V1089	FIRST NIAGARA FINL.GP.	AM	United States	Commercial Banks	
US3379151026	FIRSTMERIT	AM	United States	Commercial Banks	
US3546131018	FRANKLIN RESOURCES	AM	United States	Capital Markets	
US3602711000	FULTON FINANCIAL	AM	United States	Commercial Banks	
US38141G1040	GOLDMAN SACHS GP.	AM	United States	Capital Markets	•
US4436831071	HUDSON CITY BANC.	AM	United States	Thrifts & Mortgage	
US4461501045	HUNTINGTON BCSH.	AM	United States	Commercial Banks	
US4508281080	IBERIABANK	AM	United States	Commercial Banks	
US4590441030	INTERNATIONAL BCSH.	AM	United States	Commercial Banks	
US46625H1005	JP MORGAN CHASE & CO.	AM	United States	Commercial Banks	•
US4932671088	KEYCORP	AM	United States	Commercial Banks	
US55261F1049	M&T BANK	AM	United States	Commercial Banks	
US55264U1088	MB FINANCIAL	AM	United States	Commercial Banks	
US6174464486	MORGAN STANLEY	AM	United States	Capital Markets	•
US6494451031	NEW YORK COMMUNITY BANC.	AM	United States	Thrifts & Mortgage	
US6658591044	NORTHERN TRUST	AM	United States	Capital Markets	
US6934751057	PNC FINL.SVS.GP.	AM	United States	Commercial Banks	
US7127041058	PEOPLES UNITED FINANCIAL	AM	United States	Thrifts & Mortgage	
US7429621037	PRIVATEBANCORP	AM	United States	Commercial Banks	
US7547301090	RAYMOND JAMES FINL.	AM	United States	Capital Markets	
US7591EP1005	REGIONS FINL.NEW	AM	United States	Commercial Banks	
US78442P1066	SLM	AM	United States	Diversified Fin'l	
US78486Q1013	SVB FINANCIAL GROUP	AM	United States	Commercial Banks	
US8085131055	CHARLES SCHWAB	AM	United States	Capital Markets	
US8574771031	STATE STREET	AM	United States	Capital Markets	•
US8679141031	SUNTRUST BANKS	AM	United States	Commercial Banks	
US8690991018	SUSQUEHANNA BCSH.	AM	United States	Commercial Banks	
US87161C5013	SYNOVUS FINANCIAL	AM	United States	Commercial Banks	
US8722751026	TCF FINANCIAL	AM	United States	Commercial Banks	
US87236Y1082	TD AMERITRADE HOLDING	AM	United States	Capital Markets	
US9027881088	UMB FINANCIAL	AM	United States	Commercial Banks	
US9029733048	US BANCORP	AM	United States	Commercial Banks	
US9042141039	UMPQUA HOLDINGS	AM	United States	Commercial Banks	
US9197941076	VALLEY NATIONAL BANCORP	AM	United States	Commercial Banks	
US9388241096	WASHINGTON FEDERAL	AM	United States	Thrifts & Mortgage	
US9478901096	WEBSTER FINANCIAL	AM	United States	Commercial Banks	
US9497461015	WELLS FARGO & CO	AM	United States	Commercial Banks	•
US97650W1080	WINTRUST FINANCIAL	AM	United States	Commercial Banks	
US9897011071	ZIONS BANCORP.	AM	United States	Commercial Banks	
JP3902900004	MITSUBISHI UFJ FINL.GP.	AS	Japan	Commercial Banks	•
JP3890350006	SUMITOMO MITSUI FINL.GP.	AS	Japan	Commercial Banks	•
JP3429200003	SHINKIN CENTRAL BANK PF.	AS	Japan	Commercial Banks	
JP3805010000	FUKUOKA FINANCIAL GP.	AS	Japan	Commercial Banks	
JP3842400008	HOKUHOKU FINL. GP.	AS	Japan	Commercial Banks	
JP3105040004	AIFUL	AS	Japan	Diversified Fin'l	
JP3107600003	AKITA BANK	AS	Japan	Commercial Banks	
JP3108600002	ACOM	AS	Japan	Diversified Fin'l	
JP3152400002	BANK OF IWATE	AS	Japan	Commercial Banks	
JP3175200009	OITA BANK	AS	Japan	Commercial Banks	

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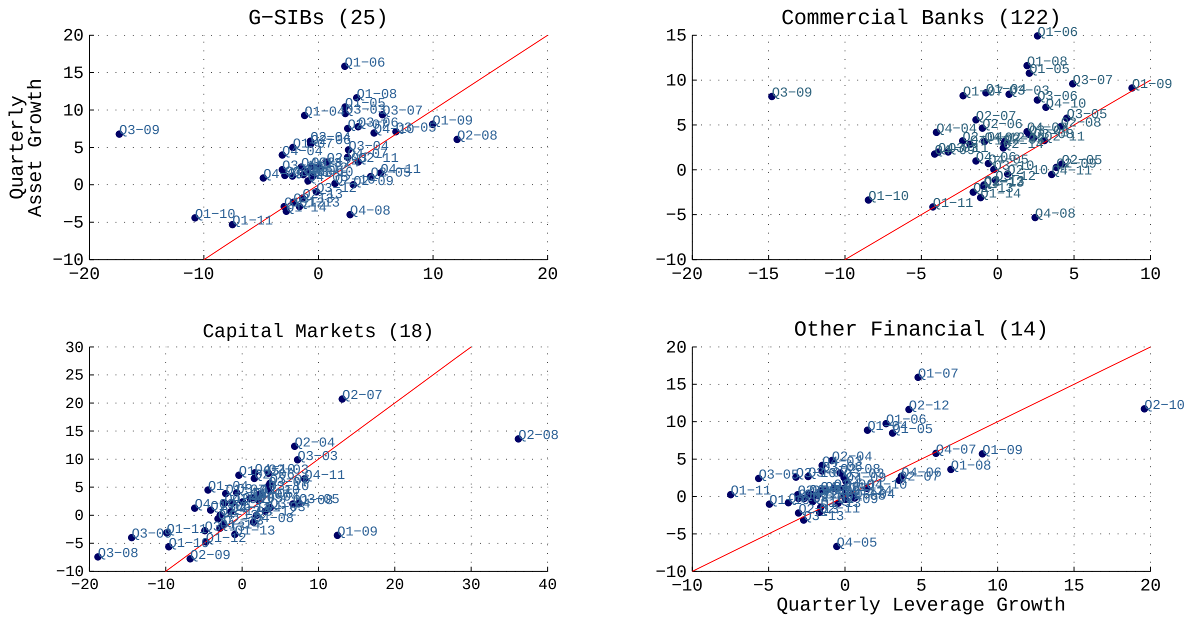
Table A.4 – continued from previous page

ISIN Code	Bank Name	Geo Code	Country	GICS Industry	G-SIB
JP3194600007	BANK OF OKINAWA	AS	Japan	Commercial Banks	
JP3200450009	ORIX	AS	Japan	Diversified Fin'l	
JP3207800008	KAGOSHIMA BANK	AS	Japan	Commercial Banks	
JP3271400008	CREDIT SAISON	AS	Japan	Diversified Fin'l	
JP3276400003	GUNMA BANK	AS	Japan	Commercial Banks	
JP3351200005	SHIZUOKA BANK	AS	Japan	Commercial Banks	
JP3352000008	77 BANK	AS	Japan	Commercial Banks	
JP3388600003	JACCS	AS	Japan	Diversified Fin'l	
JP3392200006	EIGHTEENTH BANK	AS	Japan	Commercial Banks	
JP3392600007	JUROKU BANK	AS	Japan	Commercial Banks	
JP3394200004	JOYO BANK	AS	Japan	Commercial Banks	
JP3441600008	TAIKO BANK	AS	Japan	Commercial Banks	
JP3502200003	DAIWA SECURITIES GROUP	AS	Japan	Capital Markets	
JP3511800009	CHIBA BANK	AS	Japan	Commercial Banks	
JP3520000005	CHUKYO BANK	AS	Japan	Commercial Banks	
JP3521000004	CHUGOKU BANK	AS	Japan	Commercial Banks	
JP3587000005	TOKYO TOMIN BANK	AS	Japan	Commercial Banks	
JP3601000007	TOHO BANK	AS	Japan	Commercial Banks	
JP3630500001	TOMATO BANK	AS	Japan	Commercial Banks	
JP3653400006	NANTO BANK	AS	Japan	Commercial Banks	
JP3762600009	NOMURA HDG.	AS	Japan	Capital Markets	
JP3769000005	HACHIJUNI BANK	AS	Japan	Commercial Banks	
JP3783800000	HIGO BANK	AS	Japan	Commercial Banks	
JP3786600001	HITACHI CAPITAL	AS	Japan	Diversified Fin'l	
JP3841000007	HOKUETSU BANK	AS	Japan	Commercial Banks	
JP3881200004	MIE BANK	AS	Japan	Commercial Banks	
JP3888000001	MICHINOKU BANK	AS	Japan	Commercial Banks	
JP3905850008	MINATO BANK	AS	Japan	Commercial Banks	
JP3942000005	YAMANASHI CHUO BK.	AS	Japan	Commercial Banks	
JP3955400001	BANK OF YOKOHAMA	AS	Japan	Commercial Banks	

Notes: In the first column are the ISIN identification codes followed by the institution's name, geographical location and country of reference. The last column highlights the subset of institutions which have been classified as Global Systemically Important Banks (G-SIBs) previously known as G-SIFIs (Systemically Important Financial Institutions); the classification has been adopted by the Financial Stability Board starting from November 2011 and lastly updated in November 2013.

Figure A.3: Quarterly asset growth over quarterly leverage growth across different global financial institutions



Note: he red line in each subplot is the 45 degree line. Clockwise, from top left panel, the relationship between balance sheet size and leverage for GISBs, commercial banks, institutions operating in capital markets and other financial institutions. The classification matches GICS industry codes for each entry in the sample. Source: Datastream, authors calculations.

B Dynamic Factor Model for World Risky Asset Prices – For Online Publication

Let p_t be an n-dimensional vector collecting monthly (log) asset price series $p_{i,t}$, where $p_{i,t}$ denotes the price for asset i at date t. We assume

$$p_t = \Lambda F_t + \xi_t \ . \tag{B.1}$$

F_t is an $(r \times 1)$ vector of common factors ($F_t = [f_{1,t}, \ldots, f_{r,t}]'$) that capture systematic sources of variation among prices and are loaded via the coefficients in Λ that determine how each price series reacts to the common shocks. ξ_t is a $(n \times 1)$ vector of idiosyncratic shocks $\xi_{i,t}$ that capture series-specific variability or measurement errors. We allow elements in ξ_t to display some degree of autocorrelation while we rule out pairwise correlation between assets assuming that all the co-variation is accounted for by the common component. Both the common factors and the idiosyncratic terms are assumed to be zero mean processes.

The factors are assumed to follow a VAR process of order p

$$F_t = \Phi_1 F_{t-1} + \ldots + \Phi_p F_{t-p} + \varepsilon_t, \tag{B.2}$$

where the autoregressive coefficients are collected in the p matrices $\Phi_1, \ldots, \Phi_p$, each of which is $(r \times r)$; the error term ε_t is a normally distributed zero mean process with covariance matrix Q. Any residual autocorrelation is captured by the idiosyncratic component which we assume being a collection of independent univariate autoregressive processes.

In order to distinguish between comovements at different levels of aggregation we model asset prices such that each series is a function of a global factor, a regional factor and an idiosyncratic term. We do so by allowing the vector of common shocks to include both aggregate shocks that affect all series in y_t, and shocks that affect many but not all of them:

$$p_{i,t} = \lambda_{i,g} f_t^g + \lambda_{i,m} f_t^m + \xi_{i,t} \ . \tag{B.3}$$

In Eq. (B.3) the common component ΛF_t is separated into a global factor (f_t^g) and a regional or market-specific factor (f_t^m) which is meant to capture commonalities among many but not all price series. Each $p_{i,t}$ is thus a function of a global factor loaded by all the variables in p_t, a regional or market-specific factor only loaded by those series in p_t that belong to the (geographical or sector-specific) market m, and of a series-specific factor.

Such hierarchical structure is imposed via zero restrictions on some of the elements in

Λ. In particular, we assume the common component to be partitioned into a global and several regional factors. To this aim, let the variables in y_t be such that it is possible to univocally allocate them in B different blocks or regions and, without loss of generality, assume that they are ordered according to the specific block they refer to such that $y_t = [y_t^1, y_t^2, \ldots, y_t^B]'$. Eq. (B.1) can be rewritten as

$$p_t = \begin{pmatrix} \Lambda_{1,g} & \Lambda_{1,1} & 0 & \cdots & 0 \\ \Lambda_{2,g} & 0 & \Lambda_{2,2} & & \vdots \\ \vdots & \vdots & & \ddots & 0 \\ \Lambda_{B,g} & 0 & \cdots & 0 & \Lambda_{B,B} \end{pmatrix} \begin{pmatrix} f_t^g \\ f_t^1 \\ f_t^2 \\ \vdots \\ f_t^B \end{pmatrix} + \xi_t. \tag{B.4}$$

Moreover, further restrictions are imposed on the coefficient matrices in Eq. (B.2) such that Φ_i $(i, \ldots, p)$ and Q are block diagonal.

The model in Eq. (B.1-B.2) can be cast in state space form and the unknowns consistently estimated via Maximum Likelihood (Doz et al., 2011; Engle and Watson, 1981; Reis and Watson, 2010; Bańbura et al., 2011). The algorithm is initialized using principal component estimates of the factors that are proven to provide a good approximation of the common factors when the cross sectional dimension is large.[37] We estimate the model on the price series in (log) difference and obtain the factors via cumulation.[38] We set the number of lags in the factors VAR (p) to be equal to 1. We fit to the data a model with one global and one factor per block/market; the parametrization is motivated by the results in Table B.2.

We fit the model to a vast collection of prices of different risky assets. The geographical areas covered are North America (US and Canada), Latin America (Brazil, Chile, Colombia, and Mexico), Europe (Euro Area, UK, Switzerland and the Scandinavian Countries), Asia Pacific (Japan, Hong Kong, Singapore, Korea, Taiwan), and Australia. The set of commodities considered does not include precious metals. The time span covered is from January 1990 to December 2012. In order to select the series that are included in the global set we proceed as follows: first, for each market, we pick a representative market index (i.e. S&P) and all of its components as of the end of 2012, we then select those that allow us to cover at least 80% of the cross sectional observations by the beginning of 1990, and such that by 1995 we reach a 95% coverage.[39] The procedure allows us to build

[37] Forni et al. (2000); Bai and Ng (2002); Stock and Watson (2002b,a) among others.

[38] Let $\tilde{x}_t \equiv \Delta x_t$ denote the first difference for any variable x_t, then consistent estimates of the common factors in F_t can be obtained by cumulating the factors estimated from the stationary, first-differenced model: $\tilde{p}_t = \Lambda \tilde{F}_t + \tilde{\xi}_t$. In particular, $\hat{F}_t = \sum_{s=2}^t \hat{\tilde{F}}_s$ and $\hat{\xi}_t = \sum_{s=2}^t \hat{\tilde{\xi}}_s$. Bai and Ng (2004) show that $\hat{F}_t$ is a consistent estimate of F_t up to a scale and an initial condition F_0.

[39] While estimating the Dynamic Factor Model using Maximum Likelihood does not constrain us to

Table B.1: Composition of asset price panels

	North America	Latin America	Europe	Asia Pacific	Australia	Cmdy	Corporate	Total
1975:2010	114	–	82	68	–	39	–	303
1990:2012	364	16	200	143	21	57	57	858

Note: Composition of the panels of asset prices used for the estimation of the global factor. Columns denote blocks/markets in each set, while the number in each cell corresponds to the number of elements in each block.

a final dataset with an overall cross-sectional dimension of $n = 858$. The composition is reported in Table B.1, where each category (in columns) corresponds to one of the blocks (m) within the structure imposed.

Although all series included in the set are priced in US dollars, we verify that the shape of the global factor is not influenced by this choice by estimating the same model on price series in their local currencies (i.e. the currency in which the assets are originally traded). The resulting global factor (not shown) is very similar to the one constructed from the dollar-denominated set both in terms of overall shape and of peaks and troughs that perfectly coincide throughout the time span considered. Intuitively, the robustness of the estimate of the global factor with respect to currency transformations comes directly from the structure imposed in Eq. (B.3). The blocks/markets structure imposed roughly coincides with currency areas, therefore this aspect is likely to be largely captured by the regional factors (see Table B.1).

B.1 The Number of Factors

To choose the number of global factors we use a number of criteria and tests, collected in Table B.2. The table reports the percentage of variance that is explained by the i-th eigenvalue (in decreasing order) of both the covariance matrix and the spectral density matrix, the information criteria in Bai and Ng (2002), where the residual variance of the idiosyncratic component is minimized subject to a penalty function increasing in r, and the test developed in Onatski (2009), where the null of $r - 1$ factors is tested against the alternative of r common factors. The largest eigenvalue alone, in both the time and frequency domain, accounts for about 60% of the variability in the data in the longer set and about a fourth of the variation in the shorter, but more heterogeneous set; similarly, the IC criteria reach their minimum when one factor is used, and the overall picture is confirmed by the the p-values for the Onatski test.

work with a fully balanced panel, we want to ensure that none of the categories included in the set is overrepresented at any point in time.

Table B.2: Number of Global Factors.

r	% Covariance Matrix	% Spectral Density	IC_p1	IC_p2	IC_p3	Onatski (2009) Test
			(a) 1975:2010			
1	0.662	0.579	-0.207	-0.204	-0.217	0.015
2	0.117	0.112	-0.179	-0.173	-0.198	0.349
3	0.085	0.075	-0.150	-0.142	-0.179	0.360
4	0.028	0.033	-0.121	-0.110	-0.160	0.658
5	0.020	0.024	-0.093	-0.079	-0.142	0.195
			(b) 1990:2012			
1	0.215	0.241	-0.184	-0.183	-0.189	0.049
2	0.044	0.084	-0.158	-0.156	-0.169	0.064
3	0.036	0.071	-0.133	-0.129	-0.148	0.790
4	0.033	0.056	-0.107	-0.102	-0.128	0.394
5	0.025	0.049	-0.082	-0.075	-0.108	0.531

Note: For both sets and each value of r the table shows the % of variance explained by the r-th eigenvalue (in decreasing order) of the covariance matrix of the data, the % of variance explained by the r-th eigenvalue (in decreasing order) of the spectral density matrix of the data, the value of the IC_p criteria in Bai and Ng (2002) and the p-value for the Onatski (2009) test where the null of $r-1$ common factors is tested against the alternative of r common factors.

C Bayesian VAR – For Online Publication

Let Y_t denote a set of n endogenous variables, $Y_t = [y_{1t}, \ldots, y_{Nt}]'$, with n potentially large, and consider for it the following VAR(p):

$$Y_t = \mathrm{c} + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + u_t. \tag{C.1}$$

In Eq. (C.1) c is an $(n \times 1)$ vector of intercepts, the n-dimensional A_i $(i = 1, \ldots, p)$ matrices collect the autoregressive coefficients, and u_t is a normally distributed error term with zero mean and variance $\mathbb{E}(u_t u_t') = \Sigma$. We estimate the VAR using standard macroeconomic priors (Litterman, 1986; Kadiyala and Karlsson, 1997; Sims and Zha, 1998; Doan et al., 1983; Sims, 1993). We use a Normal-Inverse Wishart prior for the VAR coefficients. To reduce the explanatory power of the initial observations (conditional on which the estimation is conducted) and of the deterministic component thus implied, we add the "sum-of-coefficients" prior in Doan et al. (1983) with the modification in Sims (1993) to allow for cointegration.

The Normal-Inverse Wishart prior takes the following form:

$$\Sigma \sim \mathcal{W}^{-1}(\Psi, \nu) \tag{C.2}$$

$$\beta|\Sigma \sim \mathcal{N}(b, \Sigma \otimes \Omega) \tag{C.3}$$

where β is a vector collecting all the VAR parameters, i.e. $\beta \equiv vec([\mathrm{c}, A_1, \ldots, A_p]')$. The degrees of freedom of the Inverse-Wishart are set such that the mean of the distribution exists and are equal to $\nu = n + 2$, Ψ is diagonal with elements ψ_i which are chosen to be a function of the residual variance of the regression of each variable onto its own first p lags. More specifically, the parameters in Eq. (C.2) and Eq. (C.3) are chosen to match the moments for the distribution of the coefficients in Eq. (C.1) defined by the Minnesota priors:

$$\mathbb{E}[(A_i)_{jk}] = \begin{cases} \delta_j & i = 1, j = k \\ 0 & otherwise \end{cases} \qquad \mathbb{V}ar[(A_i)_{jk}] = \begin{cases} \frac{\lambda^2}{i^2} & j = k \\ \frac{\lambda^2}{i^2}\frac{\sigma_k^2}{\sigma_j^2} & otherwise, \end{cases} \tag{C.4}$$

where $(A_i)_{jk}$ denotes the element in row (equation) j and column (variable) k of the coefficients matrix A at lag i ($i = 1, \ldots, p$). When $\delta_j = 1$ the random walk prior is strictly imposed on all variables; however, for those variables for which this prior is not suitable we set $\delta_j = 0$ as in Bańbura et al. (2010). On the right hand side of Eq. (C.4), the variance of the elements in A_i is assumed to be proportional to the (inverse of the) square of the lag (i^2), and to the relative variance of the variables.

The priors are implemented via the addition of dummy observations in the spirit of Theil and Goldberger (1961). Let $\gamma \equiv [\lambda, \mu, \tau]'$ be the vector of hyperparameters controlling the overall tightness of the priors. We use λ for the Normal-Inverse Wishart prior, μ for the sum-of-coefficients prior, and τ for the cointegration prior. We follow Giannone et al. (2015) and treat the γ as an additional model parameter which we estimate in the spirit of hierarchical modelling.

D Proxy SVAR and Narrative Instrument – For Online Publication

D.1 Identification with External Instruments

Let the structural representation of Eq. (C.1) be

$$B_0^{-1} Y_t = \mathrm{c} + B_1 Y_{t-1} + \ldots + B_p Y_{t-p} + e_t, \tag{D.1}$$

Table C.1: variance decomposition: selected variables

	0	1	4	8	12	16	20
USGDP	0	0.02	4.41	11.54	16.81	17.27	16.02
GDPDEF	0	0.02	0.05	0.33	1.38	2.55	3.43
GDC	0	0.12	0.58	0.95	1.91	3.56	5.62
FEDFUNDS	74.39	67.29	48.71	29.74	20.58	17.14	15.99
GCB	3.03	4.44	5.06	5.54	8.90	12.40	14.01
GCNB	3.49	3.88	3.20	1.85	1.38	1.65	2.47
BDLEV	0.30	0.91	2.16	1.91	1.75	1.63	1.62
EURLEVQ	0.24	1.35	3.31	2.94	2.65	2.54	2.69
GBPLEVQ	0.00	0.94	2.36	3.04	2.72	2.57	2.58
GFAC	0.55	1.45	1.01	1.22	2.14	2.18	2.08

Note: The table reports the forecast error variance decomposition (% points) in the baseline BVAR(4), for the variables listed in Table 1 under the recursive identification. Relevant forecast horizons in columns.

where the reduced-form autoregressive coefficients are such that $A_i = B_0 B_i$, $i = 1, \ldots, n$, and the VAR innovations

$$u_t = B_0 e_t. \tag{D.2}$$

We estimate the relevant entries of B_0 using an external instrument z_t that is assumed to be correlated with the structural shocks of interest but uncorrelated with all other structural shocks (Mertens and Ravn, 2013; Stock and Watson, 2012).

The identifying assumptions are

$$\mathbb{E}(z_t e'_{1,t}) = \kappa \qquad\qquad \mathbb{E}(z_t e'_{2,t}) = 0, \tag{D.3}$$

where $e_{1,t}$ is the shock of interest (e.g. monetary policy shock in our case) and $e_{2,t}$ contains all the other shocks. Let $\mathbf{S}_{xy}$ denote $\mathbb{E}(x_t y'_t)$ and partition B_0 such that:

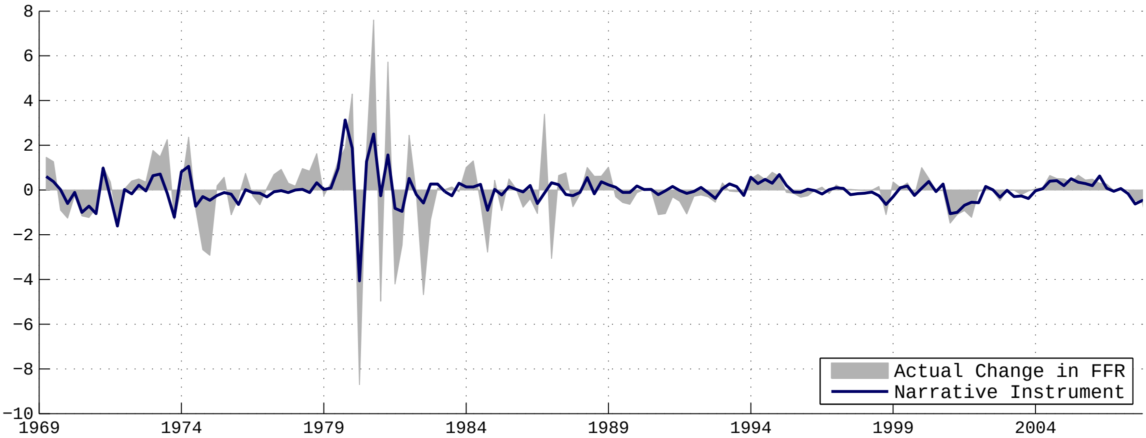
$$B_0 = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix},$$

then conditions in Eq. (D.2) and (D.3) imply that

$$b_{21} b_{11}^{-1} = \mathbf{S}_{zu'_1}^{-1} \mathbf{S}_{zu'_2}. \tag{D.4}$$

Eq. (D.4) establishes that the ratio $b_{21} b_{11}^{-1}$ can be estimated using only moments of observables; in particular, the estimate of $\mathbf{S}_{zu'_1}^{-1} \mathbf{S}_{zu'_2}$ corresponds to the two stages least square estimator in a regression of $u_{2,t}$ on $u_{1,t}$, where z_t is used as an instrument for $u_{1,t}$.

FIGURE D.1: NARRATIVE INSTRUMENT



Note: Narrative-based instrument for monetary policy shock in the US (light blue line) versus actual changes in the Federal Fund Rates (blue dotted line) over the same sample.

D.2 Narrative Instrument

We construct our external instrument by extending the narrative series first proposed in Romer and Romer (2004) (RR04 henceforth) until the end of 2007. The original series covered the period 1969-1996.

The narrative-based instrument for the monetary policy shock is constructed as the residual of the following regression (Eq. (1) in RR04):

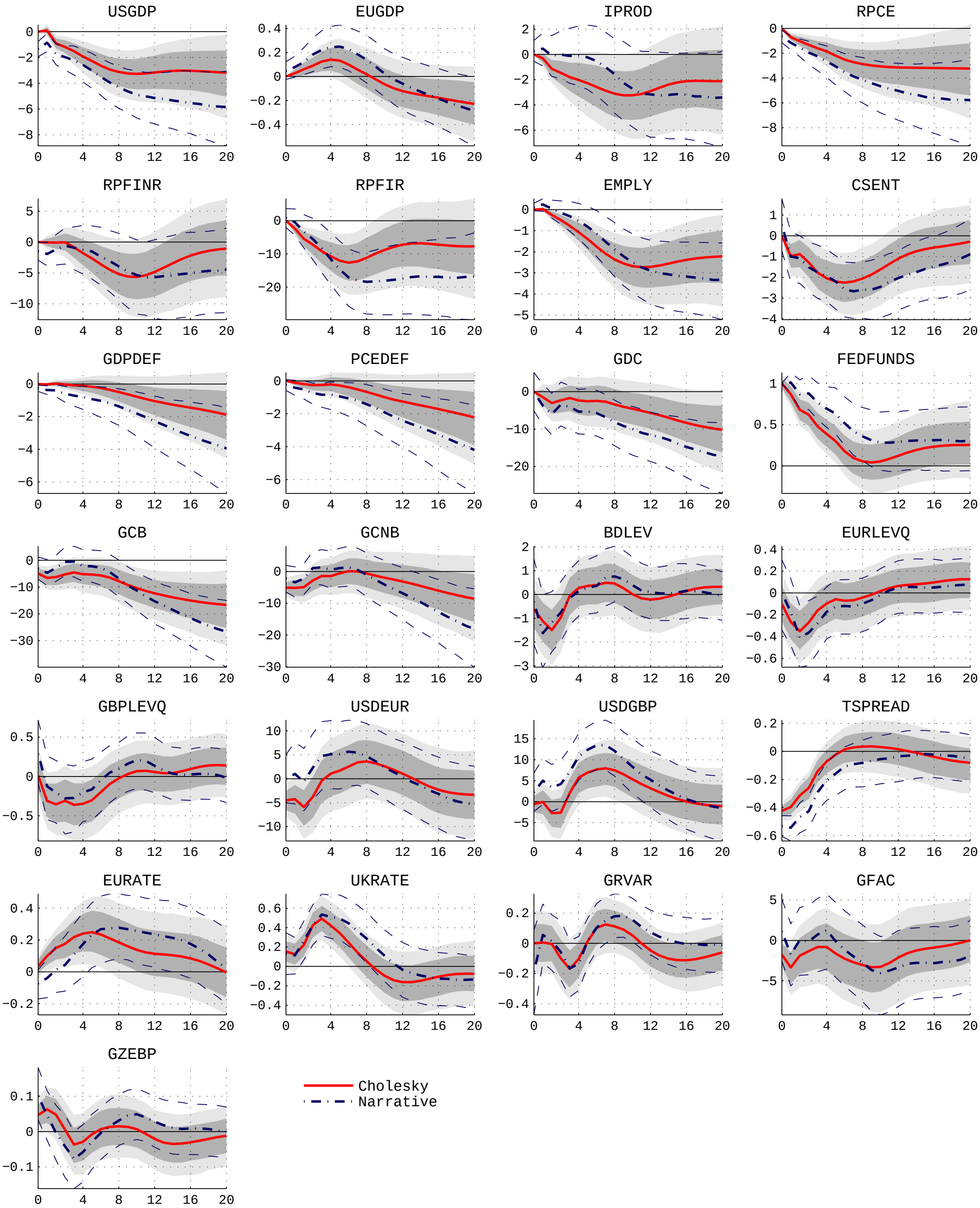
$$\begin{aligned}\Delta FFR_m =& \alpha + \beta FFR_m + \rho u^{(m)}_{t+0|t} \\ &+ \sum_{j=-1}^{2} \gamma_j y^{(m)}_{t+j|t} + \sum_{j=-1}^{2} \lambda_j \left[y^{(m)}_{t+j|t} - y^{(m-1)}_{t+j|t} \right] \\ &+ \sum_{j=-1}^{2} \phi_j \Delta\pi^{(m)}_{t+j|t} + \sum_{j=-1}^{2} \theta_j \left[\Delta\pi^{(m)}_{t+j|t} - \Delta\pi^{(m-1)}_{t+j|t} \right] + \varepsilon_m. \end{aligned} \tag{D.5}$$

Eq. (D.5) is estimated at FOMC meeting dates (indexed by m). ΔFFR_m is the change in the intended funds rate around the FOMC meeting while FFR_m is the level of the rate before any change associated to the meeting m takes place. u, y and π are used to denote the unemployment rate, real output growth and inflation respectively, while the notation $t+j|t$ denotes forecasts for quarter $t+j$ where t is the quarter the specific FOMC meeting m belongs to, such that $y^{(m)}_{t+1|t}$ denotes the forecast for real output growth (y), relative to the next quarter ($t+1|t$), which is available at meeting m.

At the time of the construction of the instrument (February 2014) Greenbook forecasts were available only up to the end of 2007, hence our sample ends at this date. Data relative to the fed funds rate level at each FOMC meeting date for the subperiod 1997-2007 are from Bloomberg. Following RR04, we obtain our quarterly instrument by summing up the residuals of Eq. (D.5) over the observations relative to the meeting dates belonging to each specific quarter. The variable is plotted in Figure D.1 against the actual changes in the federal funds rate.

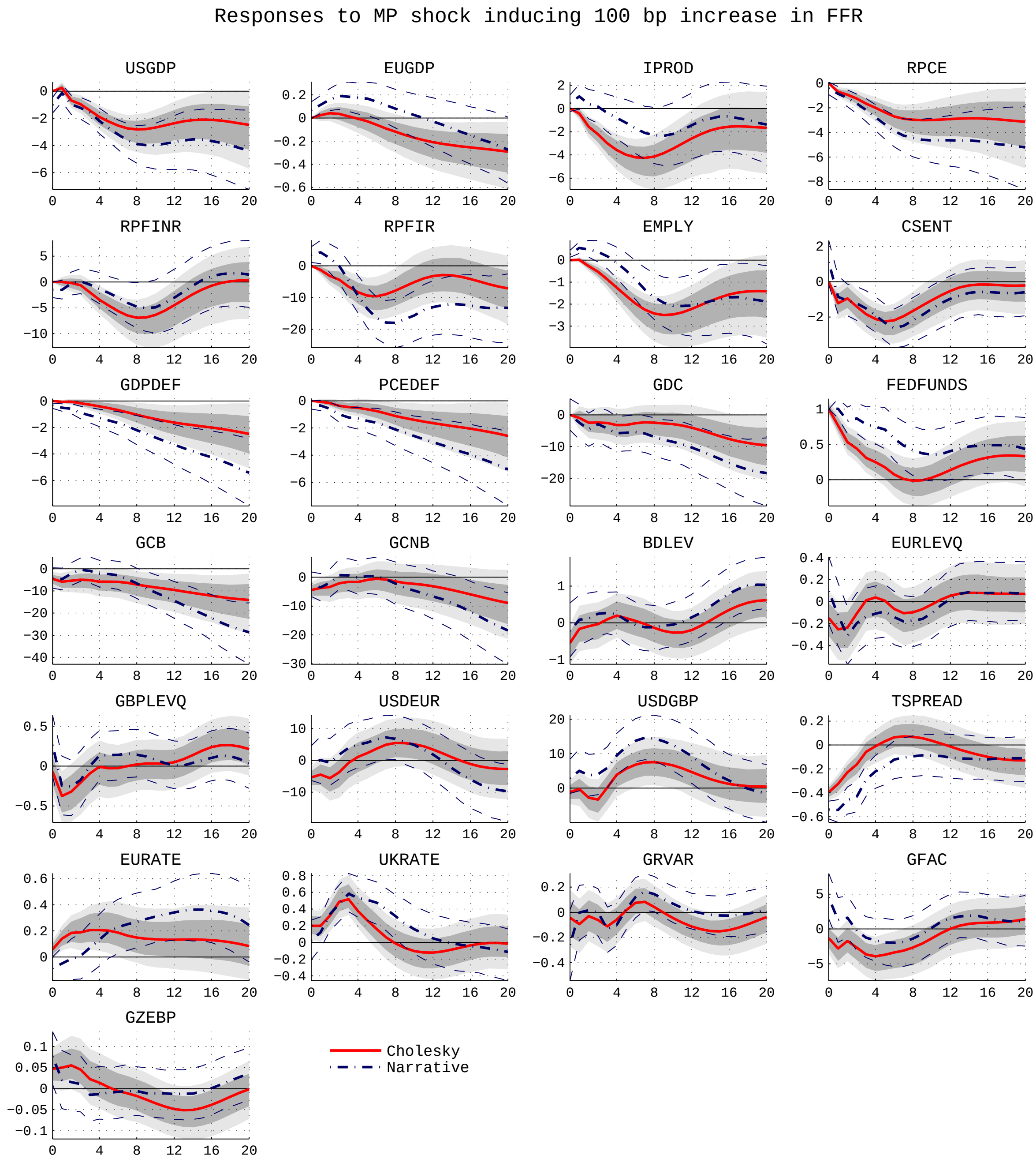
E Other Charts – For Online Publication

Figure E.1: full set of responses - baseline set



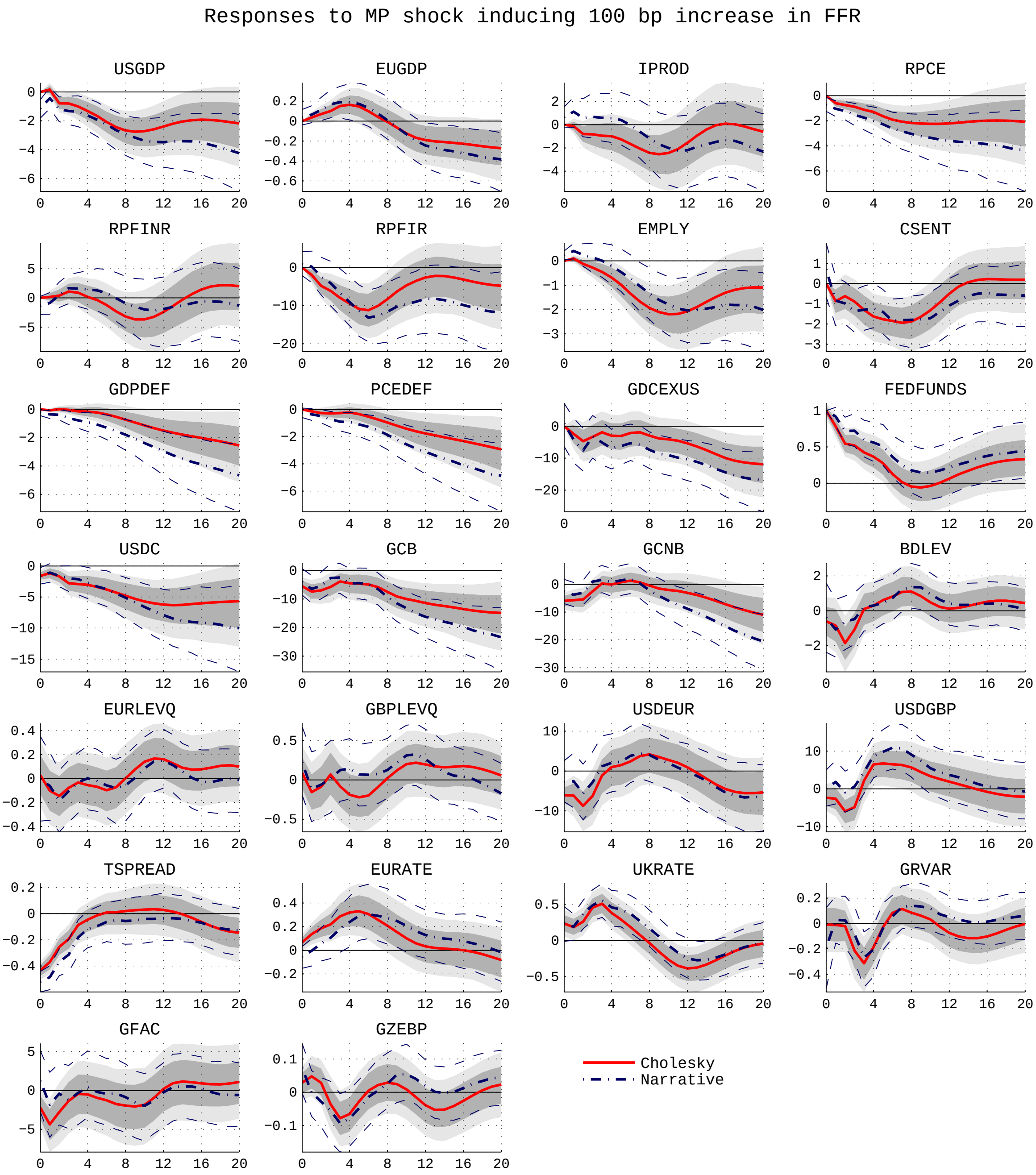
Note: Responses to a US contractionary monetary policy shock that induces a 1% increase in the fed funds rate. [red lines and grey areas] Recursive identification with 68% and 90% posterior coverage bands. [blue lines] Identification with narrative series as external instrument and 68% intervals.

Figure E.2: full set of responses - 1980-2007



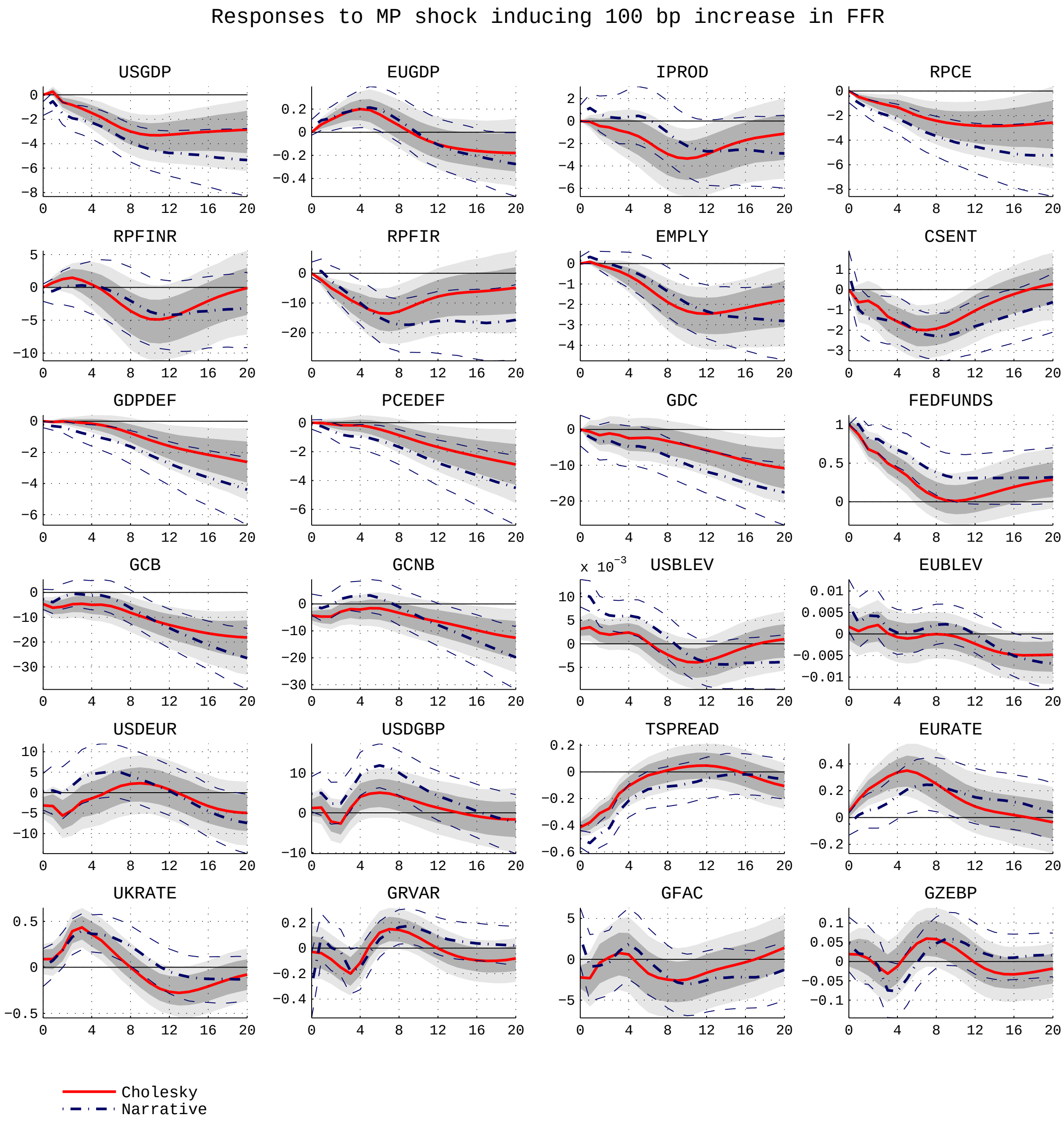
Note: Responses to a US contractionary monetary policy shock that induces a 1% increase in the fed funds rate. [red lines and grey areas] Recursive identification with 68% and 90% posterior coverage bands. [blue lines] Identification with narrative series as external instrument and 68% intervals.

Figure E.3: full set of responses - credit split



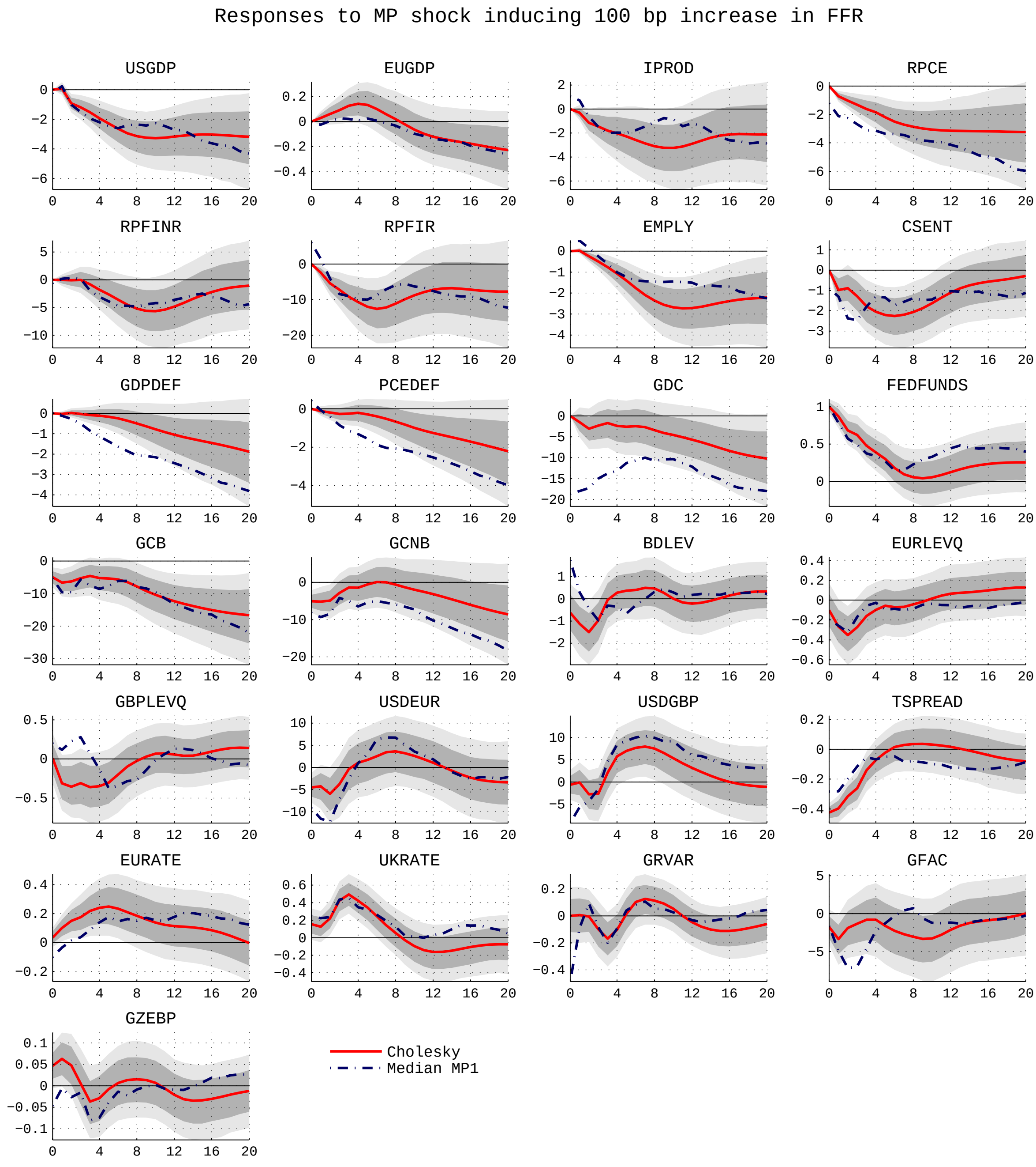
Note: Responses to a US contractionary monetary policy shock that induces a 1% increase in the fed funds rate. [red lines and grey areas] Recursive identification with 68% and 90% posterior coverage bands. [blue lines] Identification with narrative series as external instrument and 68% intervals.

Figure E.4: full set of responses - leverage split



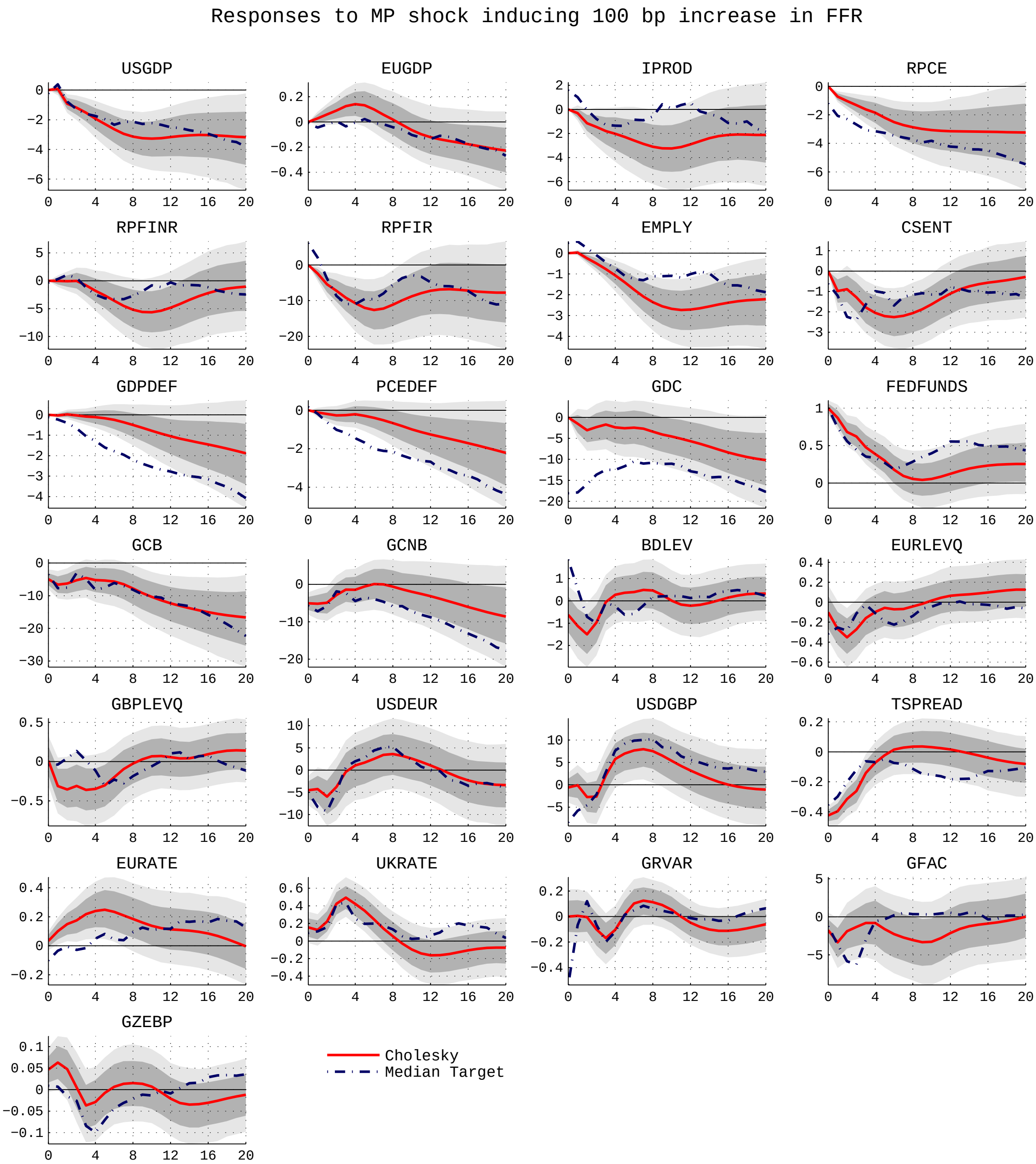
Note: Responses to a US contractionary monetary policy shock that induces a 1% increase in the fed funds rate. [red lines and grey areas] Recursive identification with 68% and 90% posterior coverage bands. [blue lines] Identification with narrative series as external instrument and 68% intervals.

Figure E.5: full set of responses - MP1 instrument



Note: Responses to a US contractionary monetary policy shock that induces a 1% increase in the fed funds rate. [red lines and grey areas] Recursive identification with 68% and 90% posterior coverage bands. [blue lines] Identification with narrative series as external instrument and 68% intervals.

Figure E.6: full set of responses - Target Factor instrument



Note: Responses to a US contractionary monetary policy shock that induces a 1% increase in the fed funds rate. [red lines and grey areas] Recursive identification with 68% and 90% posterior coverage bands. [blue lines] Identification with narrative series as external instrument and 68% intervals.