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WORLD ASSET MARKETS AND THE GLOBAL FINANCIAL CYCLE

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ABSTRACT

We find that one global factor explains an important part of the variance of a large cross section of returns of risky assets around the world. Using a model with heterogeneous investors, we interpret the global factor as reflecting aggregate realised variance and the time-varying degree of market-wide risk aversion. A medium-scale Bayesian VAR allows us to analyse the workings of the "Global Financial Cycle", i.e. the interaction between US monetary policy, real activity and global financial variables such as credit spreads, cross-border credit flows, bank leverage and the global factor in asset prices. We find evidence of large monetary policy spillovers from the US to the rest of the world.

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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 globalisation is upon us in a historically unprecedented way – we have probably surpassed the pre-WWI era of financial integration celebrated by Keynes in "The Economics Consequences of the Peace". The rising importance of cross-border financial flows and holdings have been abundantly documented in the literature (see Lane and Milesi-Ferretti, 2007 and, for a recent survey, Gourinchas and Rey, 2013). What has not been explored as much, however, are the consequences of financial globalisation for the workings of national financial systems. What are the effects of large flows of credit and investments crossing borders on fluctuations in risky asset prices in national markets and on the synchronicity of credit growth and leverage in different economies? How do large international flows of money affect the international transmission of monetary policy? Using quarterly data covering the past three decades and a stylised guiding theoretical framework, this paper seeks to analyse the effect of financial globalisation on the workings of national financial systems and the propagation of monetary policy conditions across borders.

The paper main contributions are (i) to document the existence of a global factor in risky asset prices and to suggest a structural decomposition of this factor into fluctuations in market-wide effective risk aversion and volatility using a simple stylised model with heterogenous investors; (ii) to investigate the effect of US monetary policy on standard real-economy-variables such as inflation, industrial production, consumption and investment, but also on global asset returns, credit growth, cross border capital flows and leverage using a medium-scale Bayesian VAR. We find evidence of a "Global Financial Cycle" (see Rey, 2013). There is a powerful transmission channel of US monetary policy across borders via credit flows, leverage of banks, risk premia and the term spread, emphasising the need for international macroeconomic models where financial intermediaries play an important role.

Our first set of findings concerns the "Global Financial Cycle": a very large panel of risky asset returns all around the globe is well approximated by a Dynamic Factor Model with one global factor and a set of regional factors. In other words, returns on stocks and corporate bonds exhibit a high degree of comovement worldwide. A simple model suggests that this global factor reflects both aggregate volatility of asset markets and the time-varying degree of risk aversion of markets. In turn, this aggregate risk aversion can be interpreted as reflecting the investment preferences and constraints of heterogeneous investors, for example leveraged global banks and asset managers such as insurance companies or pension funds. Global banks are assumed to be risk-neutral and to operate under a Value-at-Risk (VaR) constraint, while asset managers are risk-averse mean-variance investors. When global banks are the main investors, aggregate risk aversion tends to be low and risk premia are small. From an empirical perspective, our estimates show in particular that the aggregate degree of risk aversion in world markets declined continuously from 2003 to the beginning of 2007 to reach very low levels, at a time when the leverage of global banks was increasing sizeably.

Our second set of findings is that US monetary policy has a significant effect on the leverage of US and European investors (particularly continental European and UK banks who have large capital market operations and are classified as systemically important banks), on cross-border credit flows and on credit growth worldwide. It also has a powerful effect on the global factor and on measures of the risk premium and the term spread. At the same time, we find textbook responses for the effect of monetary policy on industrial production, GDP, consumer prices, consumer sentiment, housing investment.[1] This points towards important effects of US monetary policy on the world financial system and the Global Financial Cycle: US monetary policy is a major influence on credit conditions worldwide in terms of volumes and prices. Our results are not driven by the crisis period: this indicates that the 2007 crisis, while having had unquestionable disruptive effects on the financial markets has not altered the fundamental macroeconomic dynamics and

[1] This set of findings would not have been possible without using recent developments in the BVAR literature (see Bańbura et al., 2010; Giannone et al., 2015), as they allow us to overcome the curse of dimensionality and to estimate meaningful responses for the joint dynamics of the real economy and international financial variables (more than twenty variables). Unlike the previous literature, this makes our results far less exposed to the omitted variable problem.

transmission channels of monetary policy. This result is a challenge for the Mundellian Trilemma, a well-known proposition stating, in particular, that countries with flexible exchange rates are insulated from monetary policy spillovers via exchange rate movements and can thus pursue an independent monetary policy. We find instead that as long as capital flows across borders are not inhibited and macroprudential tools are not used to control credit growth, monetary conditions are partly dictated by the monetary policy of the centre country (the US) even for countries operating within a flexible exchange rate regime (see Rey, 2013). In other words, the Global Financial Cycle and the Mundellian Trilemma are, to some extent, incompatible with one another.

Because this paper stands at the cross-road between studies on monetary policy transmission, international spillovers via capital flows, and the role of financial intermediaries, the relevant literature is huge and cannot be comprehensively covered. Our empirical results on flows are consistent with Fratzscher (2012) (who finds an important role for "push factors" in driving financial flows using high-frequency fund data), Forbes and Warnock (2012), Rey (2013), Bruno and Shin (2015a) and Cerutti et al. (2014), who relate aggregate flow data to push factors such as the VIX. This recent literature echoes and extends earlier findings by Calvo et al. (1996) on the importance of push factors in international markets. Cetorelli and Goldberg (2012) use microeconomic data to study the role of global banks in transmitting liquidity conditions across borders. The importance of leverage as a determinant of financial instability has been studied empirically in Gourinchas and Obstfeld (2012); Schularick and Taylor (2012); Jordà et al. (2015).

Our results on the transmission mechanism of monetary policy via its impact on risk premia and the term spread are in agreement with the results of Gertler and Karadi (2015) on the credit channel of monetary policy in the domestic US context. They are also consistent with Bekaert et al. (2013), who study the impact of US monetary policy on components of the VIX and with the results of Rey (2013); Passari and Rey (2015) and Bruno and Shin (2015a) who analyse the effect of US monetary policy on leverage and on the VIX. All these studies use small scale VARs (four to seven variables) to prove their points. Lowe and Borio (2002) is an early paper which discusses the existence of financial cycles and the role of credit growth in a domestic context. Importantly, our results are also consistent with recent work by Morais et al. (2015) who, using a unique dataset at the loan level in Mexico find that a softening of foreign monetary policy increases the supply of credit of foreign banks to Mexican firms in turn implying strong real economic effects.

This paper presents a stylised static model of intermediation to set the stage for the empirical work, which constitutes the main contribution of the paper. The model builds directly on the work of Zigrand et al. (2010) and Etula (2013). A lively new literature has developed an interesting array of models of financial intermediation such as, among others, Fostel and Geanakoplos (2008); Gertler and Kiyotaki (2010); Adrian and Shin (2014); Brunnermeier and Sannikov (2014); He and Krishnamurthy (2013); Adrian and Boyarchenko (2012); Shin (2012); Bruno and Shin (2015b). This literature is related to the classic works of Bernanke and Gertler (1989); Bernanke et al. (1996); Kiyotaki and Moore (1997). All these papers have in common an emphasis on models where frictions in the financial sector are key.

To decompose fluctuations in risky asset prices into global, regional and asset-specific components we use a Dynamic Factor Model (Forni et al., 2000; Stock and Watson, 2002a,b) with loading restrictions as in Bańbura et al. (2011). The dynamic interaction between US monetary policy and the main expressions of the Global Financial Cycle are analysed within a medium scale Bayesian VAR (Bańbura et al., 2010; Giannone et al., 2015) where a standard selection of variables capturing business cycle fluctuations is augmented with a set of variables summarising the evolution of credit flows, global leverage, and a collection of financial indicators – the Global Factor, market volatility and credit costs. Results are computed under two alternative identification schemes for the monetary policy shock 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 (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), is used to identify the transmission coefficients, in a

Proxy SVAR context (Mertens and Ravn, 2013; Stock and Watson, 2012). We find that a contractionary monetary surprise reduces global banks leverage and global domestic and cross-border credit. Moreover, it is associated with a reduction in the global component of asset prices and an increase in credit costs: the term spread compresses and the excess bond premium (Gilchrist and Zakrajšek, 2012) increases at medium horizon, consistent with a credit channel effect on borrowing costs (Gertler and Karadi, 2015). Finally, a shock inducing an increase, on impact, in the US policy rate is likely to be followed by movements of the same sign – albeit of smaller magnitudes – in both the UK and the Euro Area.

The present paper differs from the literature in important ways. First, it provides an integrated framework where the existence of a global factor in international asset prices is established and analysed, and the international spillovers of US monetary policy are estimated. Second and very importantly, the use of a medium-scale Bayesian VAR allows, we believe for the first time, the joint analysis of financial, monetary and real variables interactions, in the US and abroad. Because we have all the key variables in our analysis (leverage in different geographical areas, capital flows, credit growth, asset prices, risk premia, real activity, goods prices, exchange rate, policy rates in main currency areas) the analysis gives us some insights on the mechanisms underlying international monetary policy spillovers and their magnitudes. The results should therefore inform theoretical modelling of the international transmission mechanisms of monetary policy.

We introduce a guiding theoretical framework in Section 1 and show relevant microeconomic data on banks in Section 2. We present estimates of the Dynamic Factor Model in Section 3, as well as a decomposition of the global factor in international asset prices. Section 4 performs the Bayesian VAR analysis to study the effect of US monetary policy on real activity and the Global Financial Cycle and Section 5 concludes. Details on data and additional results are in Appendixes A to E at the end of the paper.

1 The Model

Since the 1980s, and even more so the 1990s, world asset markets have become increasingly integrated with large cross-border credit, equity and bond portfolio flows. Global banks as well as asset managers have played an important role in this process of internationalisation and account for a large part of these flows. 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, sovereign wealth funds or pension funds, on the other hand. The model presented in this section is admittedly very simple and stylised. It builds straightforwardly on the work of Zigrand et al. (2010) and Etula (2013). It is there only to help us interpret the data in a transparent way, our contribution being first and foremost empirical. Like us, the recent literature emphasises the importance of financial intermediaries in asset pricing (Brunnermeier and Sannikov, 2014; He and Krishnamurthy, 2013; Adrian and Boyarchenko, 2014).

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 we assume is imposed on them by regulation. Their risk neutrality is an extreme 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 guarantee scheme, or because they are too big to fail. Whatever the microfoundations, the crisis has provided ample evidence that global banks have not hesitated to take on large amounts of risk and to lever massively. We present microeconomic evidence pertaining to their leverage and risk taking behaviour in Section 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 non 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. 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.

Global Banks

Global banks maximise the expected return of their portfolio of world risky assets subject to a Value-at-Risk constraint.[2] The VaR imposes an upper limit on the amount a bank is predicted to lose on a portfolio with a certain given probability. Following Adrian and Shin (2014), the VaR will be taken to be proportional to the standard deviation of the bank risky portfolio. We denote by $\mathbf{R}_t$ the vector of excess returns in dollars of all traded risky assets in the world. Risky assets are all tradable securities such as equities and corporate bonds. We denote by $\mathbf{x}_t^B$ the portfolio shares of a global bank. We call w_t^B the equity of the bank.

A global bank chooses its portfolio such that:

$$\max_{\mathbf{x}_t^B} \mathbb{E}_t \left(\mathbf{x}_t^{B\prime} \mathbf{R}_{t+1} \right)$$
$$s.t.\ VaR_t \leq w_t^B;$$

with the VaR_t defined as a multiple α of the standard deviation of the bank portfolio:

$$VaR_t = \alpha w_t^B \left(\mathbb{V}ar_t \left(\mathbf{x}_t^{B\prime} \mathbf{R}_{t+1} \right) \right)^{\frac{1}{2}}.$$

Writing the Lagrangian of the maximisation problem, taking the first order condition and using the fact that the constraint is binding (since banks are risk neutral) gives the

[2] 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 constraint, see Adrian and Shin (2014).

following solution for the vector of asset demands:

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

This is formally similar to the portfolio allocation of a mean variance investor. In (1), λ_t is the Lagrange multiplier: the VaR constraint plays the same role as risk aversion.[3]

Asset Managers

Asset managers are standard mean variance investors. We denote by σ their degree of risk aversion. 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 maximising:

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

hence, 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. The market clearing

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

condition for non-traded assets is:

$$\mathbf{y}_t^I \frac{w_t^I}{w_t^B + w_t^I} = \mathbf{y}_t,$$

where $\mathbf{y}_t$ is a vector of regional non-traded asset supplies. Using (1) and (2) and the market clearing conditions we can derive:

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

where $\Gamma_t \equiv \frac{w_t^B + w_t^I}{\frac{w_t^B}{\alpha\lambda_t} + \frac{w_t^I}{\sigma}}$.

Proposition 1: Risky Asset Returns

The expected excess returns on tradable risky assets can be rewritten as the sum of a global component (aggregate volatility scaled by effective risk aversion) and a regional component:

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

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. When global banks are large they will be key for the pricing of risky assets. The risk premium on risky securities is scaled up by the market effective risk aversion and depends on aggregate volatility of risky assets and on the comovement between traded and non traded assets (real estate). In Section 3 we will look at the implications of equation (3): excess returns have a global component, which is a function both of the aggregate volatility of traded risky assets and of the market effective risk aversion, and a regional one.

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*. This is equivalent to saying that 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.

2 Evidence on Global Banks

Global banks play a key role in the model as they tend to price risky assets when they are large in the markets, as in the pre-crisis period (see Shin, 2012, for the importance of global banks in international financial markets). To document empirically global banks' behaviour and their attitude toward risk, we put together a panel of monthly return indices for 166 financial institutions in 20 countries over the years from 2000 to 2010.[4] Taking as a reference the outstanding amount of total assets as of December 2010, we identify a subset of 21 large banks who have been classified as Globally Systemically Important Banks (GSIBs). The list of GSIBs, defined as those "financial institutions whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity", first compiled in November 2011, is periodically updated by the Financial Stability Board together with the Basel Committee of Banking Supervision to isolate global financial intermediaries that are systemically relevant.[5] A complete list of institutions

[4] We are by no means attempting here to test the very stylised model presented above. The model is here to set the stage and help us structure our thoughts about the data. The empirical results on the global factor and the bayesian VAR, which are the main contributions of the paper make it very clear that we still lack the theoretical apparatus to model the channels of international monetary transmission in a convincing way.

[5] http://www.financialstabilityboard.org/wp-content/r_141106b.pdf

included in our set is in Table A.4 in Appendix A.

Figure 1 reports the correlation between the beta of each bank with the global risk factor of Section 3, 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. Panels (b) and (d), which still sort the banks on the x-axis according to their pre crisis betas but report their post crisis returns, on the other hand, show, as expected, how the institutions that were loading more on the global risk pre-crisis suffered the largest losses once the meltdown began.

When banks are risk-neutral investors subject to a regulation-based VaR constraint, Adrian and Shin (2014) show that they increase leverage when measured risk is low: banks take on as much risk as allowed by the constraint. Like in the model we detailed in Section 1, low risk or improved conditions, will – other things equal – relax the VaR constraint, leading banks to borrow more and increase the size of their balance sheet. This, in turn, will increase asset demand, decrease spreads and measured risk and reinforce the feedback loop.[6] Hence, in good times, global banks increase the size of their balance sheet and transmit favourable conditions to financial markets at home and abroad (see Bruno and Shin, 2015a, for an interesting open economy analysis in partial equilibrium). Everything works in reverse in bad times.

[6]For a more complete model of this channel see Zigrand et al. (2010) or Adrian and Boyarchenko (2012). All these models study closed economies.

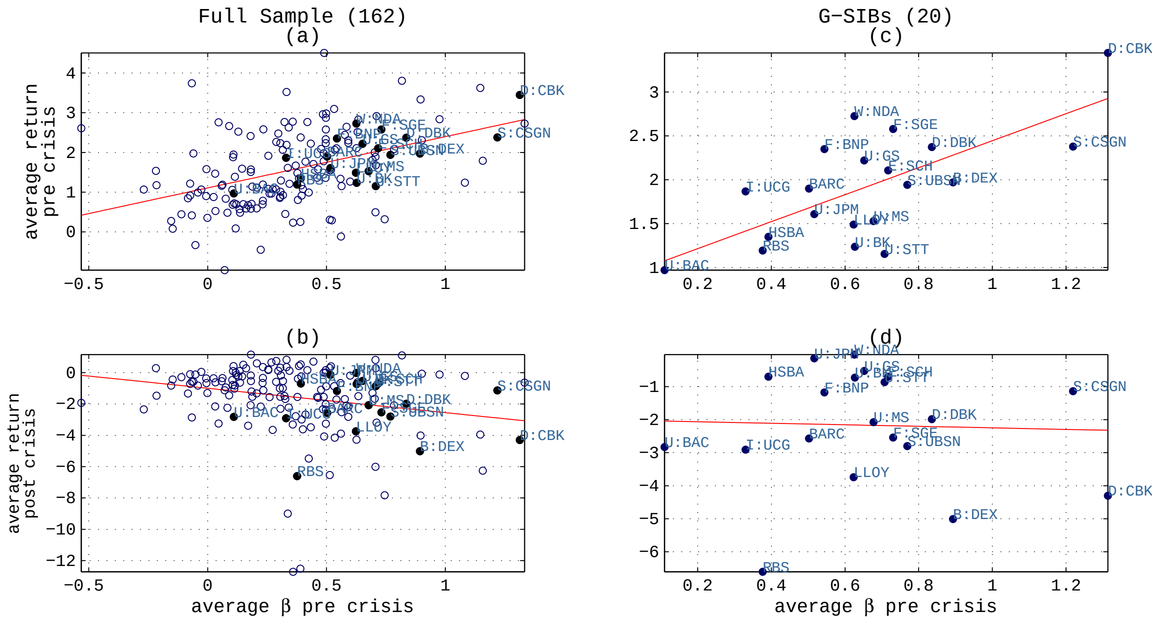

FIGURE 1: Correlation between banks' returns and their loading on the Global Factor. In each subplot, the x axis reports the average β^{BW} in the three years preceding the onset of the financial crisis (August 2007), while the y axis records average returns in percentage points. Filled blue circles highlight GSIBs within the broader population of banks considered (hollow circles); the sign of the correlation is visualised by including a red regression line in each plot. Panels (a) and (b) show the evolution of banks average returns pre (2003-2007) and post (2007-2010) crisis as a function of their pre-crisis betas. Panels (c) and (d) zoom on the relative position of GSIBs. *Source:* Datastream, authors calculations.

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 discussed above, we show in Figure 2 that the positive association between leverage and size of assets goes beyond the US borders. The charts in Figure 2 show the correlation between quarterly asset growth (percentage points, y axis) and quarterly leverage growth (percentage points, x axis) 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 includes in particular the former stand alone investment banks. The same holds true for the large European (UK, Switzerland and Euro Area) commercial banks,

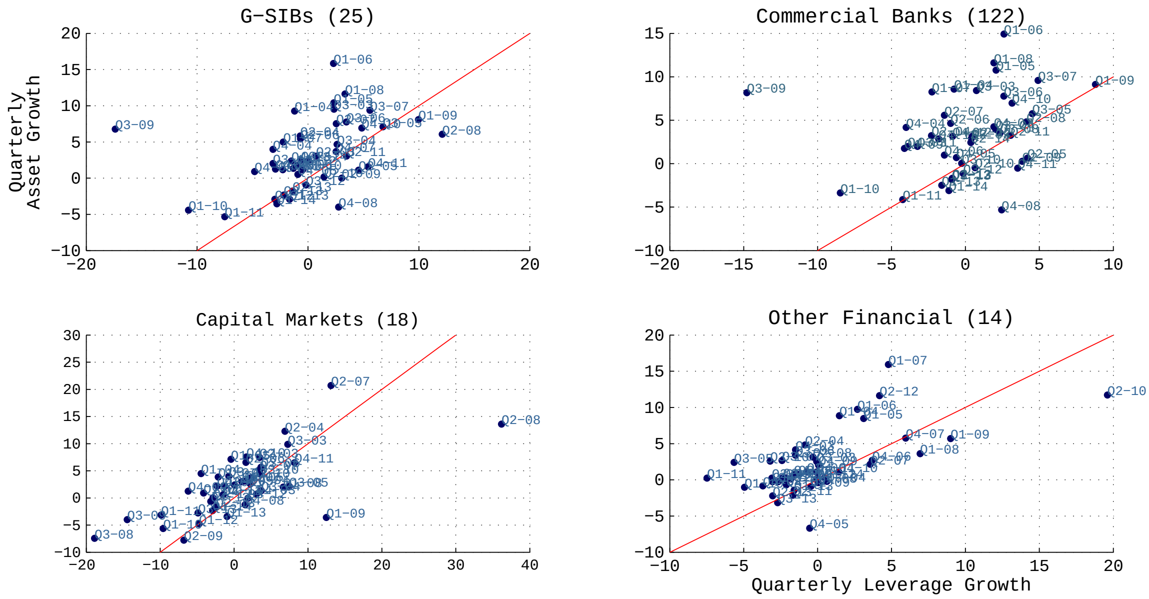

FIGURE 2: Quarterly asset growth over quarterly leverage growth across different financial institutions. The red line in each subplot is the 45 degree line. Clockwise, from top left panel, the relationship between balance sheet size and leverage for GISBs, commercial banks, institutions operating in capital markets and other financial institutions. The classification matches GICS industry codes for each entry in the sample. *Source:* Datastream, authors calculations.

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 in Appendix A).

One possible interpretation of these data, together with Figure A.1 and Figure A.2 of the Appendix documenting the growth in worldwide credit and leverage, is that banks operating in global capital markets, through leveraging and deleveraging, influence funding conditions for the global financial system and, ultimately, for the broader international economy. In particular, easier funding or particularly favourable credit conditions can translate into an increase in credit growth, reduction of risk premia and run up of asset prices. Crucial in this process is thus the attitude towards risk of international financial players that, in turn, determines their willingness to provide cross border or foreign currency financing (CGFS, 2011). Depending on their ability and willingness to take on risk, financial institutions may amplify monetary stimuli introduced by key foreign central banks, as shown using loan level data for Mexico by Morais et al. (2015). Sections

3 and 4 check the plausibility of this hypothesis by estimating the response of global financial intermediaries, asset prices and credit flows to US monetary policy shocks.

3 Global factor in risky asset returns

In this section we exploit the properties of a panel of heterogeneous risky asset prices to address empirically the implications of the model detailed in Section 1. According to equation (3) in our model, the return of a risky asset is determined by both global and asset specific factors, with the former being linked to the aggregate market volatility and the degree of risk aversion of the market. A natural way to identify empirically the components just detailed is to assume that the collection of world asset prices has a factor structure;[7] in particular, we specify the factor model such that each price series is determined by a global, a regional, and an asset specific component to isolate the underlying element that is common to all asset categories irrespective of the geographical location of the market in which they are traded or the specific asset class they belong to.

More formally, let p_t be an $N \times 1$ vector collecting monthly (log) price series $p_{i,t}$, where $p_{i,t}$ denotes the price for asset i at date t; imposing a factor structure on prices is equivalent to assume that each price series can be decomposed as:

$$p_{i,t} = \mu_i + \Lambda_i F_t + \xi_{i,t}, \tag{5}$$

where μ is a vector of N intercepts μ_i and F_t is an $[r \times 1]$ vector of r common factors that capture common sources of variation among prices. The r factors are loaded via the coefficients in Λ that determine how each price series reacts to the common shocks. Lastly, ξ_t is a $N \times 1$ vector of idiosyncratic shocks $\xi_{i,t}$ that capture price-specific variability or measurement errors. Both the common factors and the idiosyncratic terms are assumed to be zero mean processes. Price dynamics is accounted for both at aggregate and individual level; in particular, we explicitly model the dynamics of both the common and the

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

idiosyncratic component, allowing the latter 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.[8]

To identify the different elements at play, we impose further structure on the model in equation (5) and additionally decompose the common component ΛF_t into a global factor, common to all variables in our sample, and a set of regional and market-specific factors which are meant to capture commonalities among many but not all price series. More formally, each price series in p_t is modelled according to:

$$p_{i,t} = \mu_i + \lambda_{i,g} f_t^g + \lambda_{i,m} f_t^m + \xi_{i,t}. \tag{6}$$

In equation (6) $p_{i,t}$ is thus a function of the global factor (f_t^g), that is loaded by all the variables in p_t, of a regional or market-specific factor (f_t^m) that is loaded only by the series in p_t that belong to the same (geographical or asset specific) class m, and of a series-specific component.[9] In the context of the model outlined in equation (5), the implementation of the block structure in (6) is achieved by imposing restrictions on the coefficients in Λ such that the loadings for blocks to which the price variable $p_{i,t}$ does not belong to are set to zero. Similar restrictions are imposed on the matrices of coefficients governing the factors' dynamics. A detailed description of the model is reported in Appendix B where the setup, the restrictions on the parameters and the estimation procedure are all discussed.

While the overall setup adopted so far is fairly standard, factor models require the original data to be stationary, a condition that clearly does not apply to log asset prices as such. It is therefore necessary to transform first the series in p_t to achieve stationarity, and then to recover the factors in (6). To this purpose, let $\tilde{x}_t \equiv \Delta x_t$ denote the first

[8] Although this assumption might sound particularly stringent in presence of high degrees of heterogeneity in the data, it does not compromise the estimation of the model. Consistency of the Maximum Likelihood estimator is proven under this type of misspecification in Doz et al. (2011).

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

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:

$$\tilde{p}_t = \Lambda \tilde{F}_t + \tilde{\xi}_t. \tag{7}$$

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.

To ensure consistency with our theoretical formalisation, the model is applied to a vast collection of prices of different risky assets traded on all the major global markets. The geographical areas covered are North America (US and Canada), Europe (Euro Area, UK, Switzerland and the Scandinavian Countries), Asia Pacific (Japan, Hong Kong, Singapore, Korea, Taiwan), and Australia. Stacked to this set, are all major commodities price series and a collection of corporate bond indices.[10] All price series are taken at monthly frequency using end of month values to reduce the noise in daily figures while preserving the long run characteristics of the series; 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 (S&P) and all of its components as of the end of 2012, then we 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.[11] The procedure allows us to build a final dataset with an overall cross-sectional dimension of $N = 858$; the composition is reported in Table 1 below, where each identified category (in columns) corresponds to one of the blocks within the structure imposed. While in this instance we prefer cross-sectional heterogeneity over time length to be consistent with the theoretical setup detailed in Section 1, we are conscious of the limitations that a short time span might introduce in the analysis we perform later in the paper. To allow more flexibility in that respect, we repeat the estimation on a much smaller set, where only the US, Europe, Japan and commodity prices are included, and that goes back to 1975.

[10]The set of commodities considered does not include precious metals.

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

	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

TABLE 1: Composition of asset price panels. The table compares the composition of the panels of asset prices used for the estimation of the global factor; columns denote blocks in each set while the number in each cell corresponds to the number of elements in each block.See main text for details.

In each case, we fit to the data a model with one global and one factor per block. The choice is motivated by a set of results which we obtain using both formal tests and a number of different criteria. The test that we implement is the one developed by Onatski (2009), where the null of $r-1$ factors is tested against the alternative of r common factors. We complement this result with 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, 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 outcomes for both sets for the number of global factors are collected in Table 2.[12] According to the figures shown, the largest eigenvalue alone, in both the time and frequency domain, accounts for about 60% of the variability in the data belonging to 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 implemented and the overall picture is confirmed by the the p-values for the Onatski test collected in the last column.

3.1 The Global Factor

The global factors estimated from the two sets are plotted in Figure 3. The common factors are obtained via cumulation and are therefore consistently estimated only up to a scale and an initial value F_0; this implies, in practical terms, that positive and negative values displayed in the chart cannot be interpreted as such and that they do not convey any specific information *per se*. Rather, it is the overall shape and the turning points

[12]Results for the number of regional factors are not reported but available upon request.

r	% Cov Mat	% Spec Den	IC_p1	IC_p2	IC_p3	Onatski
			(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

TABLE 2: Number of Global Factors. 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.

that are of interest and deserve particular attention.

Figure 3 shows that the factor is consistent with both the US recession periods, as identified by the NBER, 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. Such increase lasts until 1997-1998 when major events like the Russian default, the LTCM bailout and the East Asian Crisis reverse the increasing path that was associated with the building up of the *dot-com* bubble. The downward trend is inverted starting from the beginning of 2003 with the index increasing again until the beginning of the third quarter of 2007 when, triggered by the collapse of the subprime market, the first signals of increased vulnerability of the financial markets become visible. This led to an unprecedented decline that has since only partially been reversed. Although all price series included in the set are taken in US dollars, we verify that the shape of the global factor is not influenced by this choice

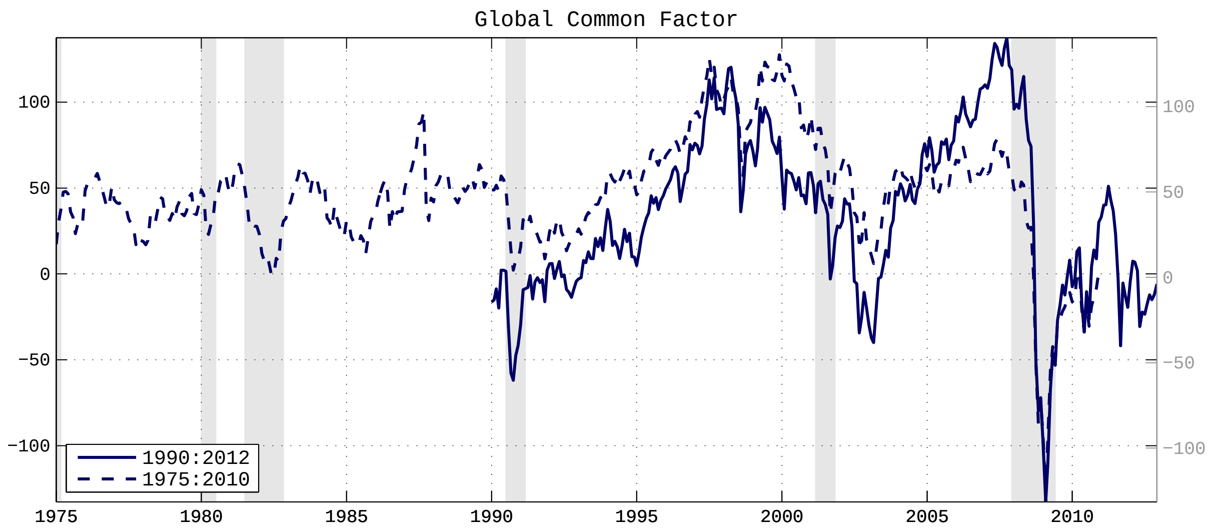

FIGURE 3: The Figure plots the estimates of the global factor for the 1975:2010 sample (dotted line) together with the estimates on the wider, shorter sample 1990:2012 (thick line). Shaded areas denote NBER recession dates.

by repeating the same exercise using a set where, instead, we leave unchanged the currency in which the assets are originally traded. The resulting global factor 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 (6); looking at Table 1 it is easy to verify that the blocks roughly coincide with currency areas and that, therefore, this aspect is likely to be captured by the regional factors.

Following the intuition detailed in Section 1, the global factor in risky asset prices should be a function of the realised market variance and of the aggregate degree of risk aversion in the market. In Figures 4 and 5 we plot the factor against other indicators which are commonly used to measure both markets uncertainty and risk aversion; as such, we expect all of them to be inversely related to our factor.[13] In Figure 4 we highlight the comovement of the factor with the volatility indices associated to the markets included in the set; specifically, the VIX for the US, VSTOXX and VFTSE for Europe and the

[13]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.

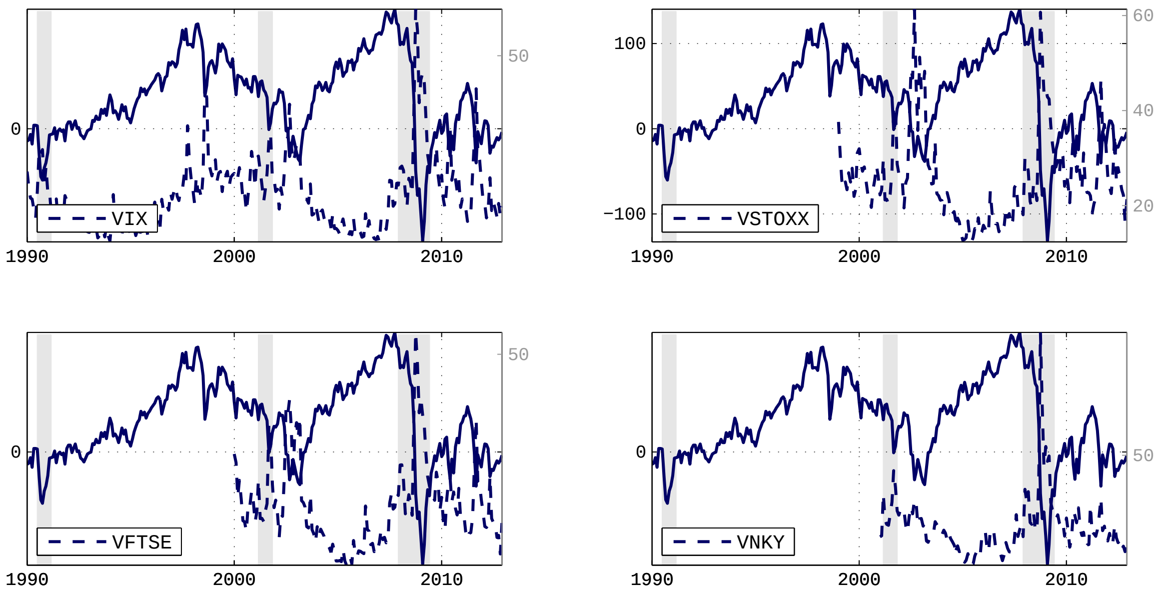

FIGURE 4: Clockwise from top-left panel, the global factor (thick line) together with major volatility indices (dotted lines); VIX (US); VSTOXX (EU); VNKY (JP) and VFTSE (UK). Shaded grey areas highlight NBER recession times.

UK respectively, and VNKY for Japan. Volatility indices are explicitly constructed to measure markets' implied volatility and reflect the expectation of future market variance; they are typically regarded as an instrument to assess the degree of strains and risk in financial markets. 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 analysed. Finally, Figure 5 compares the factor with the GZ-spread of Gilchrist and Zakrajšek (2012) and the Baa-Aaa corporate bond spread, both commonly used as measures of degree of market stress. The GZ-spread is an indicator intended to capture investors' expectation about future economic outcomes; it is constructed as a measure of borrowing costs faced by different firms, as an average of individual spreads themselves calculated as the difference between yield of corporate bonds and a corresponding risk-free security with the same implied cash flow. The three indices clearly also display some commonalities, even if the synchronicity is slightly less obvious than the one we find with respect to the volatility indices.

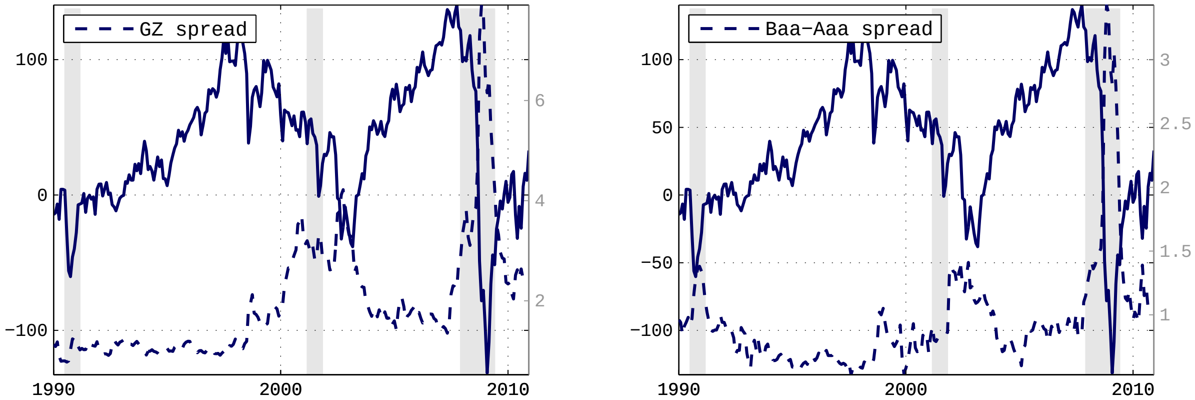

FIGURE 5: Global factor (thick line) with the GZ spread of Gilchrist and Zakrajšek (2012) [LEFT] and the Baa-Aaa Corporate bond spread [RIGHT]. Shaded grey areas highlight NBER recession times.

We finally explore the possibility of decomposing the global factor such that the global variance component is separated from the rest which, according to Section 1, should be interpreted as a time varying measure of aggregate risk aversion. We construct a raw measure of realised monthly global volatility using daily returns of the MSCI Index.[14]

In standard empirical finance applications, daily measures of realised variance are typically calculated summing over intraday squared returns sampled at very high frequency, a procedure which is shown to provide a very accurate estimation of the true, unobserved return variation (Andersen et al., 2001, 2003; Barndorff-Nielsen and Shephard, 2002; Meddahi, 2002); to reduce the distorting effects arising from too fine sampling (microstructure noise), returns are commonly calculated over a window of five minutes. For the purpose of illustrating the properties of the global factor cleared of variance effects, we work under the assumption that monthly realised variances calculated summing over daily returns provide a sufficiently accurate proxy of the global realised market variance at monthly frequency. Figure 6 summarises the results of this exercise; the top panel reports the values of the global realised variance while the inverse of the centred residual of the projection of the global factor on the realised variance is in the bottom panel. The construction of our proxy for aggregate risk aversion is modelled along the lines

[14]This approach follows from applications in e.g. Bollerslev et al. (2009) where variance risk premia are measured as the difference between implied (expectation under risk neutral probability) and realised variances.

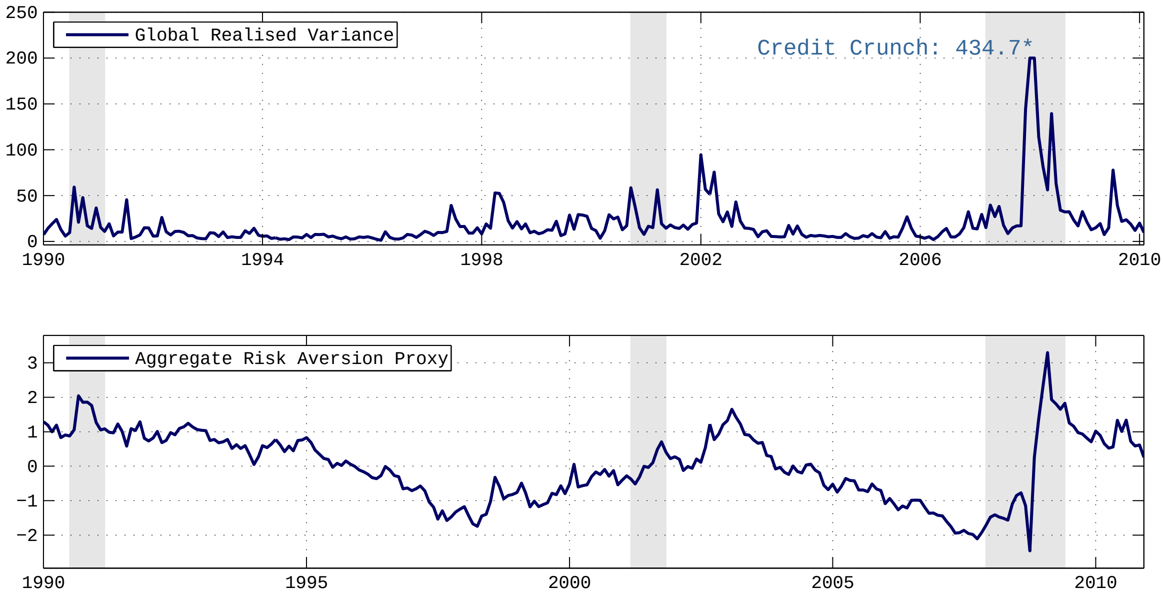

FIGURE 6: The top panel of the figure reports an index of global realised variance measured using daily returns of the MSCI Index. We limit the axis scale to enhance readability excluding periods referring to the Credit Crunch episode where the index reached a maximum of 434.70. In the bottom panel we plot an index of aggregate risk aversion calculated as (the inverse of) the residual of the projection of the global factor onto the realised variance. Shaded grey areas highlight NBER recession times.

of Bollerslev et al. (2009) and Bekaert et al. (2013) that estimate variance risk premia as the difference between a measure for the implied variance (the squared VIX) and an estimated physical expected variance which is primarily a function of realised variances. 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 to very low levels, at a time where volatility was uniformly low. It starts going up during 2007 then jumps up during the financial crisis with the failure of Lehman Brothers and remains persitently at high levels.

4 Monetary Policy and the Global Financial Cycle

Taking together the evidence discussed so far, it is natural to ask whether monetary policy could be one of the drivers of the Global Financial Cycle. More precisely, with the US dollar being the currency of global banking (see e.g. Shin, 2012), monetary actions in the US may directly influence the cycle by altering the cost of funding for major global banks as well as by affecting the pricing of dollar assets, both in the US and in other major financial markets. Furthermore, global banks can transmit monetary conditions from the centre countries through cross-border capital flows, and influence the provision of global credit (see the corroborative evidence for Mexico in Morais et al., 2015). The discussion in Section 2 further allows us to include fluctuations in asset prices in the picture, as both cause and consequence of the procyclicality of financial leverage of global banks. Prolonged periods of loose monetary policy may reduce market uncertainty and credit/funding costs, with a boost to asset prices. Rising asset prices might mask fragile foundations of expanding global banks balance sheets, since buoyant times are likely to carry low levels of aggregate risk aversion which might, in turn, induce VaR-constrained investors to build up leverage (see the "volatility paradox" in Brunnermeier and Sannikov, 2014). By the same token, however, evidence of such interactions opens up potentially powerful avenues to maintain financial stability, both locally and at a more global level.

We study the interaction between US monetary policy, leverage of global banks and the Global Financial Cycle using a medium scale Bayesian VAR. To do so, we augment the typical set of macroeconomic variables, including output, inflation, investment, consumer sentiment and labor data, with our global financial variables of interest. As far as we can tell we are the first paper who can study jointly the dynamics of the real economy, credit flows and of the Global Financial Cycle and study the effects of US monetary policy shocks on these variables in a single unified framework. To analyse the risk taking or the credit channel of monetary policy, recent empirical contributions have exclusively employed small-scale VARs. The first paper to study the links between monetary policy and risk aversion in a domestic US context is Bekaert et al. (2013) which 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 aforementioned VIX components the industrial production index and the real federal funds rate as the monetary policy variable. They find that loose monetary policy reduces both risk aversion and market uncertainty. Bruno and Shin (2015a) put together a four variable VAR with quarterly data, from the end of 1995 to the end of 2007, which feature the federal funds rate as the monetary policy variable, a measure of leverage, the VIX index and the US Dollar real effective exchange rate. A recursive Cholesky ordering is used for the identification of the monetary policy shock. The authors find that contractionary monetary policy, while increasing leverage on impact, results in a subsequent significant decrease of leverage at medium horizons and that the VIX tends to increase following a tightening. Similar findings are in Rey (2013) that also adds credit to the Bruno and Shin (2015a) set.

While these studies have the undoubted merit of addressing in a formal way the role played by monetary policy in the context of risk-building, they are nonetheless subject to an important criticism, that inevitably affects modelling choices which involve only a very small set of variables: the causal links attributed to the variables in the system might be in fact due to other variables which have been excluded from it. 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 overparametrisation, and consequent high uncertainty around parameters estimates, are a legitimate source of concern. In particular, with macroeconomic data being sampled 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 using a medium-scale Bayesian VAR as in Bańbura et al. (2010) where the informativeness of the prior is determined as in Giannone et al. (2015).[15] 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.[16]

The variables which we include in the baseline BVAR specification are listed in Table

[15] As shown in Bańbura et al. (2010), the information contained in large VARs (counting over hundred variables) can typically be recovered using much smaller medium-scale systems (of comparable size to the one used in this paper) because of the large degree of comovement among macroeconomic variables.

[16] 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.

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	•
RDPI	Real disposable personal income	•	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	•
FEDFUNDS	Effective Federal Funds Rate		MPV	
GDC	Global Domestic Credit	•	F	•
GCB	Global Inflows To Banks	•	F	•
GCNB	Global Inflows To Non-Bank	•	F	•
USBLEV	US Banking Sector Leverage		F	•
EUBLEV	EU Banking Sector 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 Realised Variance Annualised	•	F	•
GFAC	Global Factor		F	•
GZEBP	GZ Excess Bond Premium		F	

Table 3: Variables in Baseline BVAR. 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.

3 together with transformations applied prior to the estimation, and ordering for the identification of the monetary policy shock in the standard case based on causal ordering; we will also use an external proxy as a second identification scheme. The sample considered is 1980Q1 to 2010Q4.

4.1 Identification of the monetary policy shock

We present our results under two alternative identification strategies for the monetary policy shock; in the first, standard case (see e.g. Christiano et al., 1999), the identifying assumption is that it takes at least one quarter for the slow-moving variables, such as output and price indices (such as CPI, PCE deflator), to react to monetary surprises, and that the information set of the monetary authority, at the time in which decisions are taken, only includes past observations of the fast-moving ones. The second identification scheme, on the other hand, relaxes the timing restrictions which might be difficult to rationalise when, as in the present case, financial variables are also included in the conditioning set, and backs out the transmission coefficients using a proxy variable which is interpreted as an instrument for the unobserved structural shock of interest (Stock and Watson, 2012; Mertens and Ravn, 2013); the Proxy SVAR identification is discussed in more detail in Appendix D.

One of the crucial elements in the application of the proxy-variable-based identification scheme is, naturally, the choice of the instrument. Table 4 summarises a series of results which we used to guide our choice of the best instrument, conditional on the information set, sampling frequency and span of the baseline BVAR with 4 lags. The candidate instruments are all intended to capture monetary policy surprises and are constructed using different methods which, in all cases, yield what can be considered as a measure, potentially with error, of the monetary policy shock. Our first candidate is a narrative-based proxy constructed extending the narrative shock first proposed in Romer and Romer (2004) up to 2009, following the instructions detailed in Appendix D.[17] The variable captures those changes in the target federal funds rate that deviate from the intended funds rate changes set around FOMC meetings, and that are independent from monetary policy actions taken in response to information about future economic developments. Other candidate instruments are instead constructed using market-based reactions to FOMC announcements measured within a tight 30 minutes window around the announcement itself; namely, we use the Target and Path factors of Gürkaynak et al. (2005), and their underlying components, whose validity as instruments for the monetary policy shock is analysed, at monthly frequency, in Gertler and Karadi (2015).[18] In Table 4, MP1 and FF4 are the monetary policy surprises implied by changes in the current-

[17]Technically, the narrative-based measure of unexpected Federal Fund Rates changes can be extended to include more recent periods; with rates reaching the ZLB in 2009Q1, however, the interpretation of this measure becomes more problematic, therefore we decide to exclude post 2008 observations from the calculation of the instrument.

[18]Other applications of high-frequency futures data to the transmission of monetary policy shocks include among others Nakamura and Steinsson (2013) and Krishnamurthy and Vissing-Jorgensen (2011).

month and the three-months-ahead federal fund 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 instruments above; in particular, 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 (Gürkaynak et al., 2005).

The first stage in the implementation of the proxy-based identification requires regressing the VAR innovation corresponding to the monetary policy variable – FEDFUNDS in our case – onto the selected instrument. For each of the candidate instruments, Table 4 reports the t and F statistics associated to the first stage regression, a measure of the scalar reliability of the instrument, bounded between zero and 1, discussed in Mertens and Ravn (2013), and the implied correlation between the instrument and the policy shock.[19] We follow Stock et al. (2002) and require the F statistic to be above ten, for the instrument not to be considered as weak. The results displayed in the table show how, given the VAR innovations resulting from our estimates, the only instrument which is safely above the threshold is the narrative-based one. All the remaining cases are well below the critical value, even if there exists a reasonable correlation between them and the policy shock; these numbers confirm the findings of Stock and Watson (2012).[20]

Given the evidence just discussed, we think it is appropriate to drop the market-based measures and select the narrative-based surprise variable as the preferred instrument. Miranda-Agrippino (2015) performs a more detailed analysis of the use of raw market-

[19] 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).

[20] To construct quarterly surprise measures from the basic FOMC-dated series, we maintain the same assumption used for monthly instruments in both Gürkaynak et al. (2005) and Gertler and Karadi (2015) about the implied duration of each surprise; in particular, for any given quarter, the total monetary surprise is constructed as a weighted sum of the surprises registered within that quarter, where weights are proportional to the day within the quarter in which the announcement is made. In this respect, the only difference between the market-based instruments used here, and those in Gürkaynak et al. (2005); Gertler and Karadi (2015) is in the frequency of the instrument.

instrument	t stat	F stat	reliability	correlation
Narrative (07)	4.256	17.776	0.250	0.500
Narrative (09)	4.527	20.121	0.290	0.538
Target Factor	2.519	6.186	0.512	0.716
Path Factor	-0.552	0.297	0.383	0.619
MP1	2.395	5.589	0.432	0.657
FF4	2.516	6.172	0.436	0.660
ED2	2.370	5.475	0.368	0.607
ED3	2.191	4.677	0.345	0.588
ED4	1.917	3.581	0.344	0.587

Table 4: Tests for instruments validity. For each of the candidate instruments the table reports the t and F statistics associated to the first stage regression of the VAR policy innovation onto the instrument, a measure of instrument reliability, bounded between zero and 1, and the implied estimated correlation between the instrument and the monetary policy shock. Candidate instruments are: a narrative-based measure of monetary surprises constructed extending the work of Romer and Romer (2004) up to 2009 and 2007 (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 3 from 1980Q1 to 2010Q4.

based surprises as instruments for monetary policy shocks in Proxy SVARs and reaches a similar conclusion. The chosen variable is plotted in Figure 7 against the actual changes in the FFR.

4.2 Discussion of the Results

Results using both identification schemes are displayed in the form of impulse response functions (IRFs) and are obtained estimating a BVAR that includes 4 lags of the endogenous variables (using 3 and 5 lags leads to virtually identical responses). In each of the plots that follow, we report modal responses to the monetary policy shock together with 68% posterior coverage bands; the shock is normalised to induce a 100bp increase in the effective federal funds rate (EFFR).[21] In each plot, dark blue lines refer to the recursively identified monetary policy shock, whereas light blue lines are for responses obtained using the proxy-based identification with the narrative instrument. Results are robust to a number of changes in the VAR lag structure, set composition, and length

[21] While 1 standard deviation posterior coverage bands are fairly common, we verify that our results survive when 90% coverage bands are used instead.

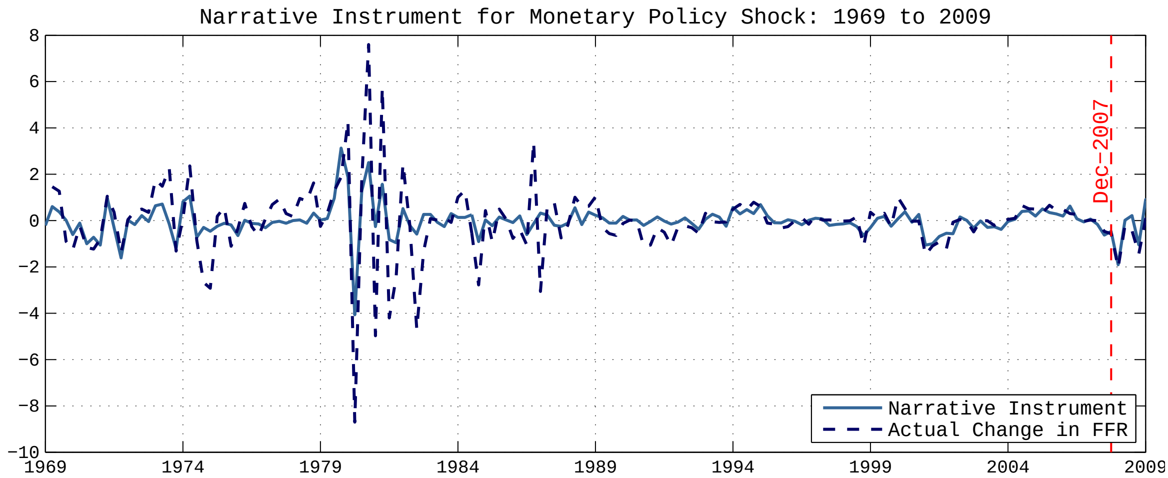

FIGURE 7: Narrative-based instrument for monetary policy shock in the US (light blue line) versus actual changes in the Federal Fund Rates (blue dotted line) over the same sample. The proxy variable is constructed at quarterly frequency as those changes in rates which deviate from intended rates set around FOMC meetings and are orthogonal to monetary intervention in response to information about current and future economic developments. The variable is constructed extending the work of Romer and Romer (2004) for the period 1969-2009; December 2007 marks a discontinuity in the methodology adopted due to data availability described in Appendix D.

of the sample considered, for which additional charts are reported in Appendix E at the end of the paper. The appendix also contains the full set of responses from which Figures 8 to 11 have been extracted. The IRFs corresponding to the narrative proxy-based identification are obtained using data for the instrument up to the end of 2007, where the endpoint is chosen to avoid the discontinuity in the methodology discussed in the appendix and the Zero Lower Bound zone which begins in 2009Q1. Results obtained using the full length of the instrument are similar, and are part of our robustness checks. A detailed description of the BVAR, estimation and priors used is in Appendix C.

The variables of interest in our analysis can be classified in three main groups. First, we look at credit provision both domestically and internationally; in both cases, 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 here intended as direct cross-border credit provided by foreign banks to both banks and non-banks in the recipient country (Avdjiev et al., 2012). Second, we look at banks' leverage. In this respect, following the differences highlighted in Section 2, we distinguish between the banking sector as a whole (baseline specification) and globally systemic US and European banks.[22] Finally, we analyse the role played by monetary policy in the context of risk building, financial stability and credit costs by looking at the responses of global asset prices (summarised by the global factor estimated in Section 3), financial market uncertainty (proxied by the index of global realised market variance described in the same Section), the term spread (calculated as the spread between the 10-year and 1-year constant maturity Treasury rates) and the GZ excess bond premium of Gilchrist and Zakrajšek (2012). Following Gertler and Karadi (2015), we measure credit costs using both the term premia and credit spreads. While in a world with frictionless financial markets, for a given maturity, the return on private securities equals that on government bonds, financial frictions create room for a credit channel in which monetary policy not only impacts borrowing rates, but also affects the external finance premium (see Gertler and Kiyotaki, 2010). Responses of these variables to a monetary policy shock are shown in Figures 8 and 9.

The responses of real economic variables to monetary policy shocks and subsequent dynamics are consistent with economic theory (see Figure E.1): US GDP, industrial production and consumption contract, and so do private residential investment, non farm payroll employment and housing starts. European GDP first increases (possibly due to an expenditure switching effect) and then contracts with delay. Price inflation whether measured by the GDP deflator or the PCE deflator goes down. Consumer sentiment declines. Importantly, the responses of both global domestic and global cross-border credit data in Figure 8 highlight how monetary actions in the US influence global financial conditions; following a monetary tightening, credit provision at a global level significantly contracts and remains low for up to five years after the shock. Results on global domestic credit are not driven merely by US data, as is visible in Figure 10, 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. Furthermore, after an initial

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

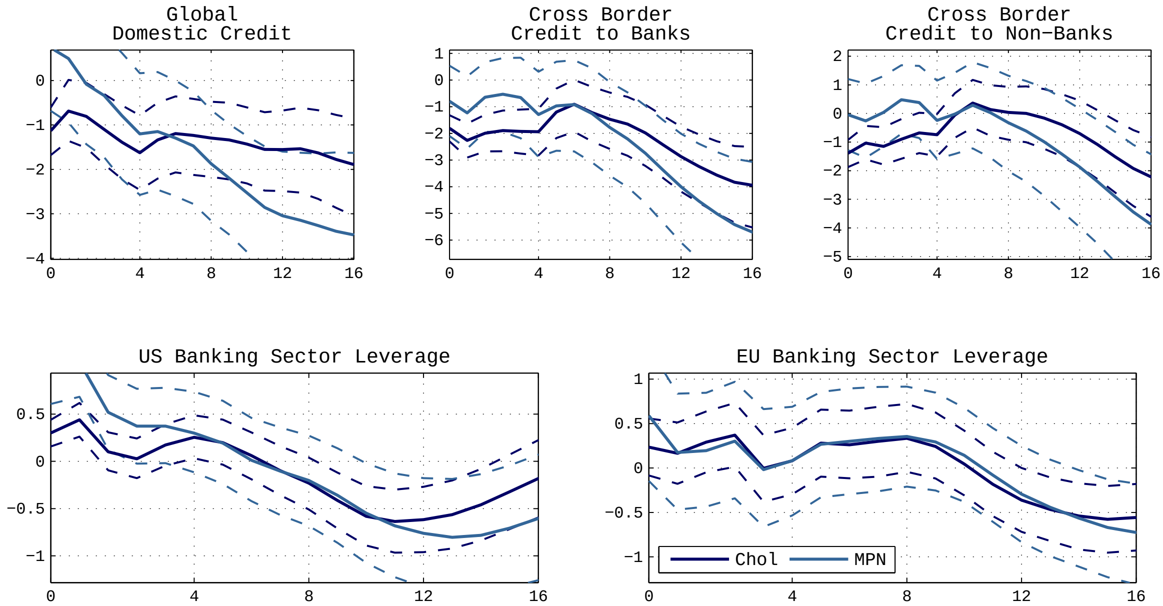

FIGURE 8: Response of global domestic credit and international cross-border credit (top row) and banking sector leverage (bottom row) to a monetary policy shock inducing a 100 basis point increase in the EFFR. Banking sector leverage is measured at country level as the ratio between claims on private sectors and deposits of depository corporations excluding central banks. Details on the construction of credit and leverage variables are in Appendix A. The chart compares responses obtained when the monetary policy shock is identified using a recursive scheme (dark blue line) with those resulting from a Proxy SVAR with narrative-based instrument (light blue line). Dotted lines limit the 68% posterior coverage bands.

increase, the leverage of US banks first and EU banks afterwards decreases significantly (Figure 8). Figure 9 shows that the global factor in world asset prices and the global realised variance have a symmetrical response to the shock, volatility compresses on impact and then increases after about 6 quarters, while asset prices significantly decrease with a lag; however, while the medium-term increase in volatility is short lived, the decrease in the global factor is markedly more persistent. Risk premia move much in the same direction as market variance; they increase at medium horizons following a contractionary monetary policy shock, while, on the other hand, the term spread decreases significantly on impact to rebound in the medium/long horizon.

The full set of results are thus coherent with the theoretical effects of monetary policy: following an unexpected tightening by the Fed, we witness a contraction of national

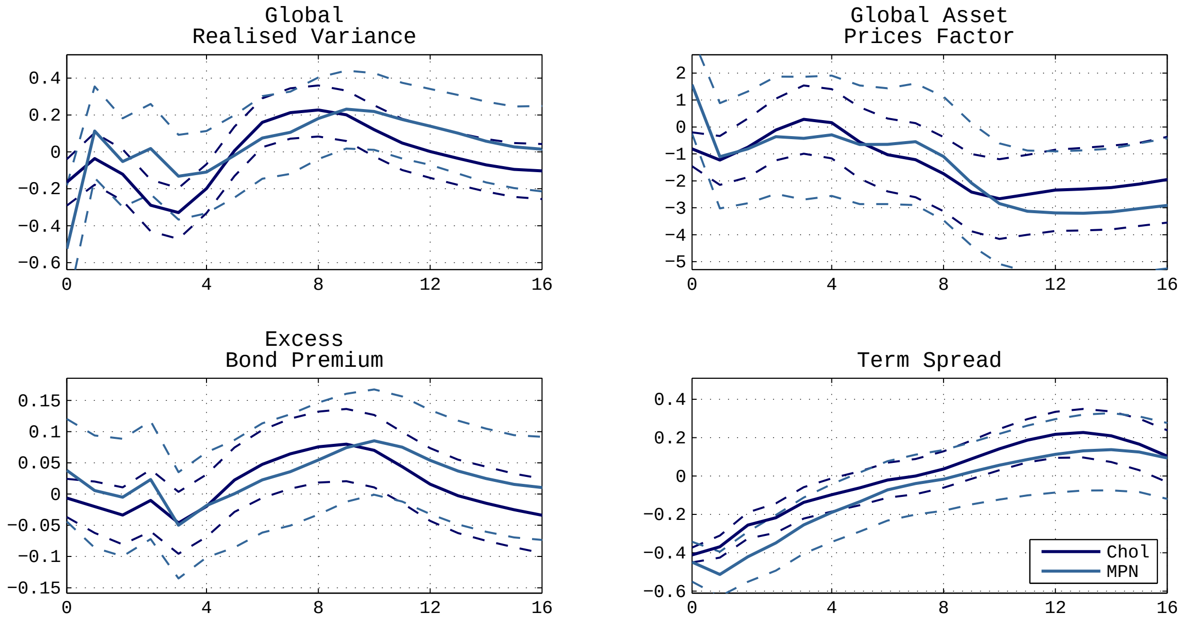

FIGURE 9: The figure highlights the role of monetary policy in the context of risk building, financial stability and credit costs. Clockwise from top left panel the plots report responses of global realized market variance, the global asset prices factor, the term spread and the GZ excess bond premium to a monetary policy shock inducing a 100 basis point increase in the EFFR. The chart compares responses obtained when the monetary policy shock is identified using a recursive scheme (dark blue line) with those resulting from a Proxy SVAR with narrative-based instrument (light blue line). Dotted lines limit the 68% posterior coverage bands.

real activity (gross output, industrial production, housing construction and employment) and prices (GDP and personal consumption expenditures deflators); furthermore, consumption and income decrease as do investment and consumers sentiment. Monetary aggregates (M2) contract, as expected, and we tend to see an appreciation of the US dollar vis-à-vis both the Euro and the Sterling on impact of about 1% going down to about 2% after 6 months (point estimate) under the recursive identification scheme. The response is however not always significant when we use the proxy VAR; exchange rates are about the only variables for which the identification scheme matters.[23] Banking sector leverage increases on impact both in the US and Europe but then significantly decreases at medium horizons; this holds true for US banks and, to a lesser extent, for European banks.

[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 rate chosen at the time of introduction of the common currency.

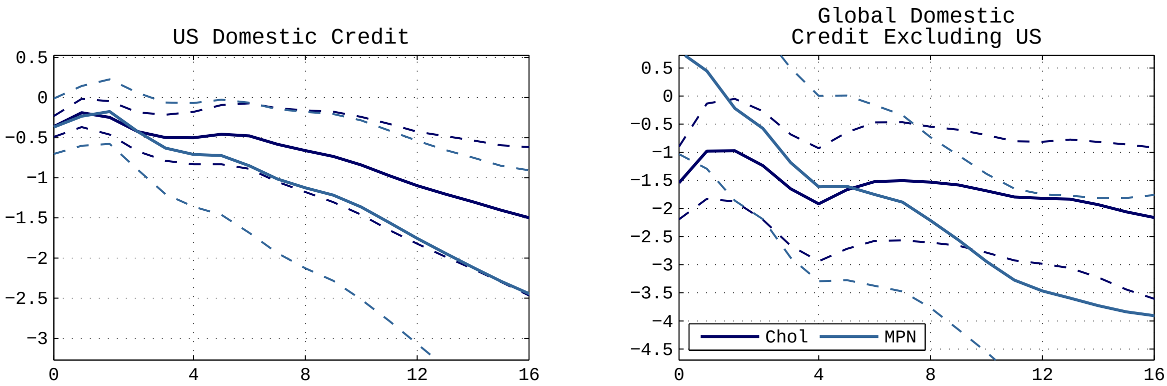

FIGURE 10: Response of global credit variables to a monetary policy shock inducing a 100 basis point increase in the EFFR. Detail on US versus ROW domestic credit measures. The responses are obtained from a BVAR(4) estimated on the set reported in Table 3 where Global Domestic Credit is split between US and rest of the world domestic credit. The complete set of responses are in Figure E.4, Appendix E. The chart compares responses obtained when the monetary policy shock is identified using a recursive scheme (dark blue line) with those resulting from a Proxy SVAR with narrative-based instrument (light blue line). Dotted lines limit the 68% posterior coverage bands.

While we display results obtained estimating the BVAR using data up to 2010Q4, with the narrative instrument built either until December 2007 (Figure E.1) or until March 2009 (Figure E.2), 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.3). 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).

Given the fundamental differences in risk attitude and balance sheet adjustments that characterize global banks with respect to national or more traditional financial institutions, in a last exercise we substitute the US and European banking sector leverage with

[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.3.

leverage ratios calculated for US Security Brokers and Dealers (USBD) and 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. Responses of these variables to a monetary shock inducing a 100bp increase in the US FFR are displayed in Figure 11. While the data limitations encountered in their calculation impose some caution in the evaluation of their responses, we find nonetheless some interesting results. Following a contractionary US monetary policy shock, these institutions, who fund themselves partly in US dollars, respond immediately by reducing their leverage, before the broader banking aggregates previously studied. The first to react are the US broker-dealers; they are then followed by the Euro Area GSIBs and, less significantly, by the UK GSIBs. As shown before, it is only after that the decrease in leverage transmits itself to the broader banking aggregates.

Lastly, and very interestingly, Figure 11 reports responses of the UK and Euro Area policy rates (bottom panels); the responses are extracted from the specification in Figure E.5, where the set in Table 3 is modified such that GSIBs leverage is substituted for the more generic banking sector leverage, but are robust to the alternative specifications reported in Figures E.1 - E.4. Results suggest that a contractionary move in the US is likely to be followed by stricter monetary policy both in the UK and the Euro Area. Increases in the policy rates are both positive and significant, and peak to about 50 and 40bp respectively, with some delay. They are consistent with both a "fear of floating" argument (see Calvo and Reinhart, 2002) and with endogenous developments in the UK and European economies.

Table 5 reports the forecast error variance decomposition for a selection of the variables included in the BVAR.[25] At first glance, the percentages shown might be interpreted as being relatively small, however, considering the number of variables included in the system, this should not be at all surprising. The assessment of the systematic component of monetary policy depends on the conditioning information set used in the analysis,

[25] Variance decomposition for the full list is reported in Table E.1 in Appendix E.

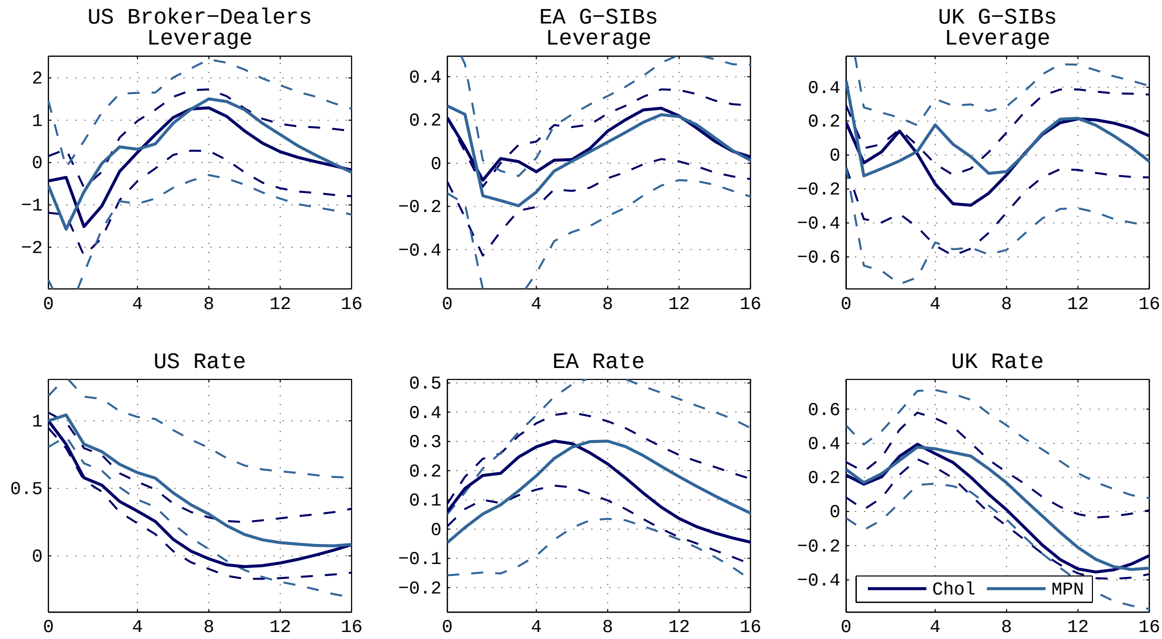

Figure 11: Response of global banks leverage (top panels) and of policy rates (bottom panels) to a monetary policy shock inducing a 100 basis point increase in the EFFR. Leverage ratios of UK and EA GSIBs are constructed as the median bank-specific leverage, in turn computed as the ratio between assets and equity, as detailed in Appendix A. The responses are obtained from a BVAR(4) estimated on the set reported in Table 3 where US and EU banking sector leverage measures are replaced with US Broker -dealers, UK and EA G-SIBs leverage ratios. The complete set of responses are in Figure E.5, Appendix E. The chart compares responses obtained when the monetary policy shock is identified using a recursive scheme (dark blue line) with those resulting from a Proxy SVAR with narrative-based instrument (light blue line). Dotted lines limit the 68% posterior coverage bands.

so it should be taken to be reasonably close to the one used by policy makers. If a plausible information set is not used, monetary policy shocks may well be confused with mis-specification errors; once, on the other hand, more realistic conditioning information sets are used, then the size of the unsystematic component of monetary policy is reduced. That said, we still find that monetary policy explains a far from trivial fraction of the forecast error variance of banks' leverage, credit flows and financial markets-related variables. We also find that the variance of the real variables such as GDP and inflation explained by the monetary policy shock increases with the horizon and reaches significant levels.

	Horizon					
	0	1	4	8	16	20
USGDP	0	0.4	1.4	4.1	12.3	13.3
EMPLY	0	0.3	0.3	0.3	5.1	9.4
GDPDEF	0	1.3	1.8	7.9	19.7	19.6
FEDFUNDS	77.8	67.2	42.4	26.5	18.2	14.6
GDC	9.1	7.9	13.1	12.1	11.5	16.0
GCB	8.9	12.9	13.9	7.3	10.0	15.6
GCNB	5.9	4.7	4.5	2.7	8.1	17.0
USBLEV	0.1	2.3	2.8	3.9	5.7	6.3
EUBLEV	1.3	2.0	2.9	2.1	5.0	5.0
TSPREAD	44.4	42.5	23.3	14.3	11.2	8.9
GRVAR	0.6	1.1	4.2	6.7	9.0	8.1
GFAC	1.3	0.8	1.8	1.7	6.5	8.8
GZEBP	0.0	0.1	3.6	5.3	6.8	6.9

Table 5: Variance Decomposition: Selected Variables. The table reports the forecast error variance decomposition in the baseline BVAR(4), for the variables listed in Table 3, when the monetary policy shock is identified under the recursive Cholesky scheme. Forecast horizons, in columns, are expressed in quarters. Shares of variance of the variables of the first column explained by the monetary innovations are expressed in percentage points.

5 Conclusions

This paper establishes the importance of US monetary policy as a driver of the Global Financial Cycle. 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. Using a stylised model we find that this factor can be interpreted as reflecting movements in aggregate volatility on world equity markets and time-varying market risk aversion. As such it is closely correlated with the VIX and similar indices in the Euro Area, the UK or Japan. We find in particular evidence of sinificant decline in effective risk aversion between 2003 and the beginning of 2007. 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. Because we use a medium-scale Bayesian VAR, we are able to look meaningfully at the joint behaviour of the real economy and international financial variables in a single comprehensive modelling framework. Responses to a monetary policy shock in the US are identified using standard recursive schemes and via external instruments in a Proxy SVAR. We perform numerous robustness checks for the specification of our VAR.

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 see also 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 very 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 reaction of monetary policy rates in the UK and in the Euro area. Hence, we find that US monetary policy is an important driver of the Global Financial Cycle.[26] 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 at all, as Klein and Shambaugh (2013) rightly point out.[27] This international transmission mechanism of monetary policy is *a priori* 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.[28] Understanding more finely the in-

[26]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.

[27]For an interesting theoretical modelling of the challenges of the trilemma even in a standard neo-Keynesian model, see Farhi and Werning, 2012, 2013). For recent empirical discussions of the Trilemma based on deviations from uncovered interest parity, see Obstfeld (2015).

[28]For a more detailed discussion of the theoretical challenges when modelling international monetary policy transmission channels, see Rey (forthcoming)

ternational transmission channels of monetary policy is, in our view, a key challenge for Central Bankers and market participants alike. It is hard to see at this point how the Global Financial Cycle and the Mundellian trilemma can fully coexist.

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A Credit and Banking Data

A.1 Domestic and Cross-Border Credit

Credit data, both domestic and cross-border, are constructed using original raw 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 below.

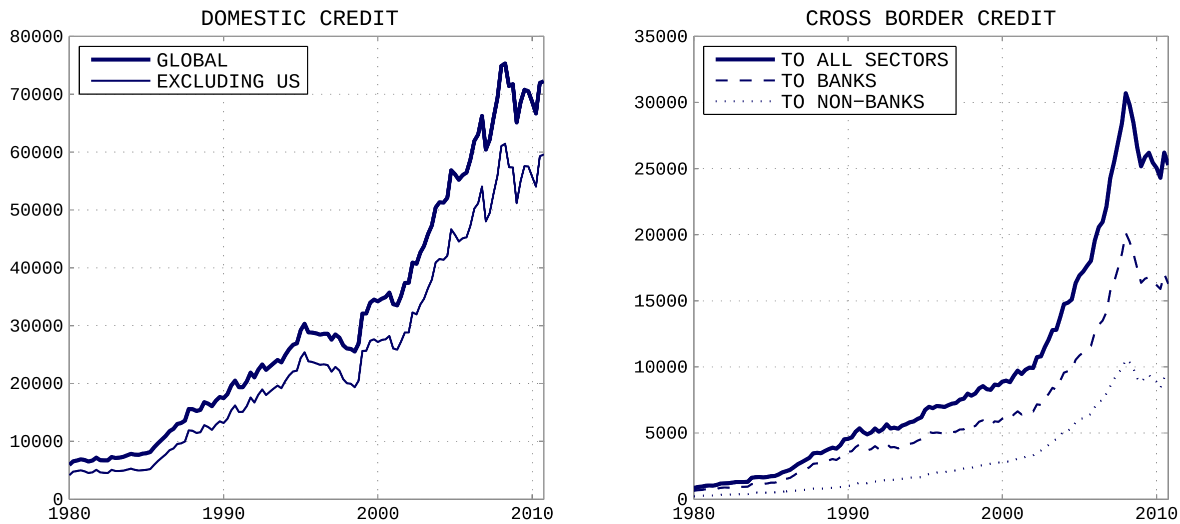

FIGURE A.1: The Figure plots Global Domestic Credit and Global Cross-Border Inflows constructed as the cross sectional sum of country-specific credit variables. The unit in both plots is Billion USD.

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 Domestic Credit is

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			

Table A.1: List of Countries Included. The table lists the 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.

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.

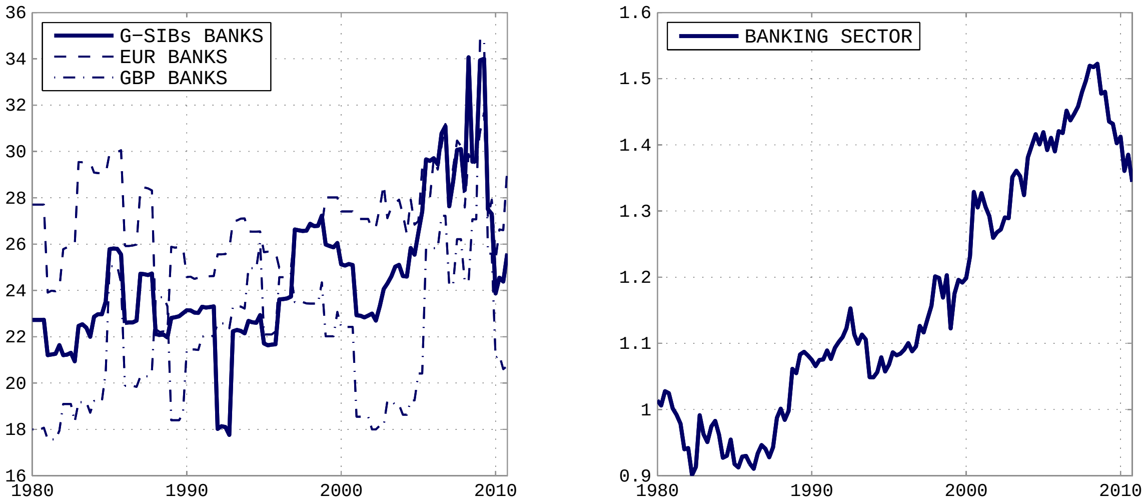

FIGURE A.2: The left panel plots the leverage ratio calculated for the European GSIBs with a detail on EUR and GBP banks using the institutions and classification in Table A.2. The right panel plots the aggregated European banking sector leverage ratio measured as the median of European countries banking sector leverage variables following Forbes (2012).

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.

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 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

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		•

TABLE A.2: European G-SIBs. The table lists the 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.

in Figure A.2.

The charts in Section 2 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).

	(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

TABLE A.3: Bank Data Summary Statistics. The table reports summary statistics for the bank-level data used in the analysis distinguishing between Total Assets (A), Shareholders' Equity (E) and Leverage Ratio (L) and grouping banks according to their GICS Industry Classification: Commercial Banks (CommB); Global Systemically Important Banks (GSIBs); Capital Markets (CapM); Thrifts & Mortgage Finance (T&MF) and Other Financial (Other Fin'l) which includes Diversified Financial Services and Consumer Finance. Total assets and common equity are in Billion USD.

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	•
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	

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Table A.4 – continued from previous page

ISIN Code	Bank Name	Geo Code	Country	GICS Industry	G-SIB
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	
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	

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ISIN Code	Bank Name	Geo Code	Country	GICS Industry	G-SIB
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	
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	

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Table A.4 – continued from previous page

ISIN Code	Bank Name	Geo Code	Country	GICS Industry	G-SIB
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: The table reports the list of financial institutions included in the set. 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.

B Dynamic Factor Model

Let y_t denote a collection of N stationary demeaned variables such that $y_t = [y_{1,t}, \dots, y_{N,t}]'$; saying that y_t has a factor structure is equivalent to formulating the following representation for the elements in it:

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

In equation (B.1) y_t is decomposed into two independent components, ΛF_t, common to all entries in y_t, and ξ_t, which is instead series-specific and is referred to as the idiosyncratic component. F_t is an $r \times 1$ vector of common factors ($F_t = [f_{1,t}, \dots, f_{r,t}]'$) that capture systematic sources of variation in the data and are loaded via the coefficients in Λ. Conversely, 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 $\Phi_1, \dots, \Phi_p$, 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 finally captured by the idiosyncratic component which we assume being a collection of independent univariate autoregressive processes:

$$\xi_{i,t} = \rho_i \xi_{i,t-1} + e_{i,t} \tag{B.3}$$

whith $e_{i,t} \sim i.i.d.N(0, \sigma_i^2)$ and $\mathbb{E}(e_{i,t}, e_{j,s}) = 0$ for $i \neq j$.

In order to distinguish between comovements at different levels of aggregation we allow 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. In particular, we assume the common component to be partitioned into a global and several regional factors. More precisely, 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 $y_t = [y_t^1, y_t^2, \dots, y_t^B]'$. Within the text we model prices such that each series is a function of a global factor, a regional factor and an idiosyncratic term; such hierarchical structure is imposed via zero restrictions on some of the elements in Λ such that equation (B.1) can be rewritten as

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

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

$$\Phi_i = \begin{pmatrix} \Phi_{i,g} & 0 & \cdots & 0 \\ 0 & \Phi_{i,1} & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \Phi_{i,B} \end{pmatrix} \qquad Q = \begin{pmatrix} Q_g & 0 & \cdots & 0 \\ 0 & Q_1 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & Q_B \end{pmatrix}.$$

The model in (B.1) to (B.3) can be cast in state space form and the unknowns consistently estimated via Maximum Likelihood using a combination of Kalman Filter/Smoother and the EM algorithm (Doz et al., 2011; Engle and Watson, 1981; Reis and Watson, 2010; Bańbura et al., 2011).[29] 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.[30] In our empirical application the number of lags in the factors VAR (p) is set to be equal to 1.

C Bayesian VAR

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):

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

[29] Doz et al. (2011) discuss consistency of the maximum likelihood estimator for a large approximate factor model. They show that traditional factor analysis is feasible in large cross-sections and that consistency is achieved even if the underlying data generating process is an approximate factor model; in particular they show that as $N, T \to \infty$ the expected value of the common factors converges to the true factors along any path.

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

In (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 Bayesian techniques to overcome the curse of dimensionality standard Maximum Likelihood estimation approaches incur when the number of variables included in the system becomes large. To do so we follow the literature and in particular set the priors as in Litterman (1986); Kadiyala and Karlsson (1997); Sims and Zha (1998); Doan et al. (1983); Sims (1993).

Litterman (1986) proposes the use of the so-called Minnesota prior which amounts to assume that the variables in the VAR follow a random walk with drift as in (C.2) below:

$$Y_t = \mathrm{c} + Y_{t-1} + u_t. \tag{C.2}$$

The prior mean implied by the Minnesota prior specified in (C.2) requires A_1 in (C.1) to shrink towards an n-dimensional identity matrix, and the elements in the remaining A_i matrices $(i = 1 + 1, \ldots, p)$ to shrink towards zero. Furthermore, this prior specification also assumes that more recent lags are more informative than distant lags and that in each equation own lags are more informative than lags of other variables. In the setting defined in Litterman (1986), however, the residual VAR variance is assumed to be diagonal, option which impairs structural analysis. To overcome this incompatibility Kadiyala and Karlsson (1997) suggest to impose a Normal-Inverse Wishart prior on the VAR coefficients which retains the main characteristics of the Minnesota prior while allowing for cross correlation among the residuals. Moreover, to reduce the explanatory power of the initial observations (conditional on which the estimation is conducted) and of the deterministic component thus implied, to the Normal-Inverse Wishart prior 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:

$$\Sigma \sim \mathcal{W}^{-1}(\Psi, \nu) \tag{C.3}$$

$$\beta | \Sigma \sim \mathcal{N}(b, \Sigma \otimes \Omega) \tag{C.4}$$

where β is a vector collecting all the VAR parameters. 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 (C.3) and (C.4) are chosen to match the moments for the distribution of the coefficients in (C.1) defined by the Minnesota priors:

$$\mathbb{E}[(A_i)_{jk}] = \begin{cases} \delta_j & i = 1, j = k \\ 0 & otherwise \end{cases} \qquad \mathbb{V}ar[(A_i)_{jk}] = \begin{cases} \frac{\lambda^2}{i^2} & j = k \\ \frac{\lambda^2}{i^2}\frac{\sigma_k^2}{\sigma_j^2} & otherwise, \end{cases} \tag{C.5}$$

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). The hyperparameter λ governs the overall tightness of the prior distribution around its mean and determines the relative importance of the prior distribution with respect to the data likelihood; with $\lambda = 0$ (maximum shrinkage) the data are not allowed to contribute any information and the posterior distribution coincides with the prior, conversely, as $\lambda \to \infty$ the prior information is discarded and the estimation approaches Maximum Likelihood. On the right hand side of (C.5), the variance of the elements in A_i is assumed to be inversely proportional to the square of the lag (i^2) involved, moreover, for variables other than the one in equation j the variance is further defined as a function of the relative variance of the variables involved.

The priors are implemented via the addition of dummy observations in the spirit of Theil (Theil and Goldberger, 1961). To this purpose, rewrite the model in (C.1) as follows:

$$\mathrm{Y} = \mathrm{X}\mathbf{B} + \mathrm{U}, \tag{C.6}$$

where $\mathrm{Y} \equiv [Y_1, \ldots, Y_T]'$ is $[T \times n]$, $\mathrm{X} = [X_1, \ldots, X_T]'$ is $[T \times (np+1)]$ with $X_t \equiv [Y'_{t-1}, \ldots, Y'_{t-p}, 1]'$, $\mathrm{U} \equiv [u_1, \ldots, u_T]'$ and $\mathbf{B} \equiv [A_1, \ldots, A_p, \mathrm{c}]'$ is $[(np+1) \times n]$ and contains all the coefficients in (C.1). The implementation of the Normal-Inverse Wishart (NIW) prior requires the addition of the following initial observations:

$$\mathrm{Y}_{NIW} = \begin{pmatrix} diag(\delta_1\sigma_1, \ldots, \delta_n\sigma_n)/\lambda \\ \mathbf{0}_{n(p-1)\times n} \\ \ldots\ldots\ldots\ldots\ldots \\ diag(\sigma_1, \ldots, \sigma_n) \\ \ldots\ldots\ldots\ldots\ldots \\ \mathbf{0}_{1\times n} \end{pmatrix} \qquad \mathrm{X}_{NIW} = \begin{pmatrix} J_p \otimes diag(\sigma_1, \ldots, \sigma_n)/\lambda & \mathbf{0}_{np\times 1} \\ \ldots\ldots\ldots\ldots\ldots & \ldots \\ \mathbf{0}_{n\times np} & \mathbf{0}_{n\times n} \\ \ldots\ldots\ldots\ldots\ldots & \ldots \\ \mathbf{0}_{1\times np} & \epsilon \end{pmatrix}. \tag{C.7}$$

In (C.7) $J_p \equiv diag(1, \ldots, p)$ and ϵ is set to be a very small number; the first block of observations defines the prior on the autoregressive coefficients, the second block concerns the coefficients in the covariance matrix and the last block imposes a very diffuse prior on the intercepts. The "sum-of-coefficients" (SoC) prior of Doan et al. (1983) and the modification introduced by Sims (1993) to allow for cointegration (Coin) are instead implemented adding the following two blocks respectively:

$$\mathrm{Y}_{SoC} = diag\left(\frac{\overline{Y}}{\mu}\right) \qquad \mathrm{X}_{SoC} = \begin{pmatrix} diag\left(\frac{\overline{Y}}{\mu}\right) & \dots & diag\left(\frac{\overline{Y}}{\mu}\right) & \mathbf{0}_{n\times 1} \end{pmatrix} \tag{C.8}$$

$$\mathrm{Y}_{Coin} = \frac{\overline{Y}'}{\tau} \qquad \mathrm{X}_{Coin} = \frac{1}{\tau}\begin{pmatrix} \overline{Y}' & \dots & \overline{Y}' & 1 \end{pmatrix}. \tag{C.9}$$

The n artificial observations in (C.8) are added on top of the data and imply that at the beginning of the sample a no-change forecast is a good forecast. $\overline{Y}$ denotes the sample average of the initial p observations per each variable and μ is the hyperparameter controlling for the tightness of this prior; with $\mu \to 0$ the prior is uninformative whereas $\mu \to \infty$ implies a unit root in each of the variables and rules out cointegration. This last characteristic of the "sum-of-coefficients" prior calls for the use of an additional artificial observation, the one defined in (C.9), which states that at the beginning of the sample a no-change forecast for all variables is a good forecast. Here the hyperparameter controlling for the variance of the prior is τ; the prior becomes uninformative when $\tau \to \infty$.

To estimate the BVAR we follow Giannone et al. (2015) and treat the hyperpriors as additional model parameters which are estimated, in the spirit of hierarchical modeling, maximizing the marginal likelihood of the data. More specifically, let θ and γ denote the vectors collecting model parameters and hyperparameters respectively. Given a choice on the on the hyperparameters γ, Bayesian inference typically works building on a prior distribution $p_\gamma(\theta)$, and data likelihood given by $p(Y|\theta)$. In the context of hierarchical modeling, however, the choice of the hyperparameters bears no difference with respect to the one concerning the elements in θ, therefore, in this setting, a prior distribution (hyperprior) is specified on γ, $p_\gamma(\theta)$ is replaced by $p(\theta|\gamma)$, and γ is chosen as the maximizer of $p(\gamma|Y) \propto p(Y|\gamma)p(\gamma)$. With flat hyperprior, this is equivalent to maximizing the marginal likelihood $p(Y|\gamma)$ which is defined as the conditional density of the data, given the hyperparameters, once the model parameters θ have been integrated out. Giannone et al. (2015) discuss the optimality of this procedure and show that maximizing the marginal likelihood is equivalent, under flat hyperprior, to maximizing the one-step-ahead out-of-sample forecasting ability of the model.

In our implementation, the hyperparameters in γ are λ defined in (C.7), μ in (C.8) and τ in (C.9). For these hyperparameters we follow Giannone et al. (2015) and choose a Gamma hyperprior with mode equal to 0.2, 1, and 1 and standard deviations equal to 0.4, 1 and 1 respectively.

D Proxy SVAR and Narrative Instrument

D.1 Proxy Structural VAR

Let the SVAR representation of the system discussed in Appendix C (equation C.1) be

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

where the set of matrices of reduced form autoregressive coefficients is such that $A_i = B_0 B_i$, $i = 1, \ldots, n$, and the VAR innovations

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

The covariance matrix of the VAR innovations – $\mathbb{E}(u_t u_t') = \Sigma = B_0 B_0'$ – allows to impose $n(n+1)/2$ restrictions, however, since B_0 has n^2 free parameters, additional restrictions are needed in order to identify the elements in B_0, even when only partial identification is being considered. Proxy SVARs (Mertens and Ravn, 2013; Stock and Watson, 2012) solve the identification issue by introducing a proxy (instrumental) variable z_t that is assumed to be correlated with the structural shocks of interest but uncorrelated with all other structural shocks in the system.

More formally, the key conditions under which identification can be achieved in this framework are:

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

where $e_{1,t}$ and $e_{2,t}$ are partitions of e_t collecting the shocks of interest and the remaining ones respectively.

Identification of the structural shocks of interest, and associated impulse response functions, is achieved in the following way; suppose $e_{1,t}$ contains only one shock and that a proxy variable z_t, such that conditions in D.3 are met, exists. 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 D.2 and D.3 imply that

$$b_{21} b_{11}^{-1} = \mathbf{S}_{zu_1'}^{-1} \mathbf{S}_{zu_2'}. \tag{D.4}$$

Equation D.4 establishes that the ratio $b_{21} b_{11}^{-1}$ can be estimated using only information coming from the proxy variable z_t and the VAR innovations u_t; 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 $u_{1,t}$. When the number of structural shocks to be identified is equal to one, the restrictions implied by the proxy variable approach yield closed form solution for the identification of the elements of interest in B_0 (Mertens and Ravn, 2013); in particular,

$$b_{11} = \left[\mathrm{Q}_{11} - (\mathrm{Q}_{21} - b_{21} b_{11}^{-1} \mathrm{Q}_{11}')' \mathbf{G}^{-1} (\mathrm{Q}_{21} - b_{21} b_{11}^{-1} \mathrm{Q}_{11}) \right]^{1/2} \tag{D.5}$$

$$\mathbf{G} \equiv b_{21} b_{11}^{-1} \mathrm{Q}_{11} (b_{21} b_{11}^{-1})' - (\mathrm{Q}_{21} (b_{21} b_{11}^{-1})' + b_{21} b_{11}^{-1} \mathrm{Q}_{21}') + \mathrm{Q}_{22}, \tag{D.6}$$

where Q_{ij}, $i, j = 1, 2$, denote appropriate partitions of the innovations covariance matrix.

D.2 Narrative Instrument

The variable which we use as an instrument for monetary policy shock in the US within the Proxy Structural BVAR framework delineated above is built as an extension of the narrative shock developed in Romer and Romer (2004) (RR04 henceforth). The new narrative-based instrument is constructed at quarterly frequency for the period 1969-2012.

The construction of the instrument closely follows the approach in RR04: the indicator variable for monetary policy is constructed as those changes in the Federal Fund Rates that deviate from the intended funds rate changes set around FOMC meeting and are independent from monetary policy actions taken in response to information about future economic developments. RR04 approximate the conditioning information set using a combination of forecasts of inflation and real activity that are available to policy makers at the time of the FOMC decision. In developing the extended version of the narrative-based instrument, we make the same working assumptions as in RR04, that is, (1) the relevant sampling frequency is dictated by the schedule of the FOMC meetings and (2) the set of forecasts used to purge the measure from macroeconomic condition considerations is a good proxy of the information set available to policy makers at the time of the decision.

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

$$\begin{aligned} \Delta FFR_m =& \alpha + \beta FFR_m + \rho u^{(m)}_{t+0|t} \\ & + \sum_{j=-1}^{2} \gamma_j y^{(m)}_{t+j|t} + \sum_{j=-1}^{2} \lambda_j \left[y^{(m)}_{t+j|t} - y^{(m-1)}_{t+j|t} \right] \\ & + \sum_{j=-1}^{2} \phi_j \Delta\pi^{(m)}_{t+j|t} + \sum_{j=-1}^{2} \theta_j \left[\Delta\pi^{(m)}_{t+j|t} - \Delta\pi^{(m-1)}_{t+j|t} \right] + \varepsilon_m . \end{aligned} \tag{D.7}$$

Equation (D.7) 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.

For the sample 1969-1996 we use the data supplied by RR04[31] where intended rates are extracted from FOMC minutes and the forecasts used are the Greenbook forecasts. To work out the extension up to 2012 we proceed as follows; at the time of the construction of the instrument (February 2014) Greenbook forecasts[32] were available only up to the end of 2007, therefore, for the subperiod 1997-2007, we simply extend the RR04 dataset using the same data sources and the same methodology. Following that date, (subsample 2008-2012) we substitute the Greenbook forecasts with those available from the Philadelphia Fed in the form of Survey of Professional Forecasts[33,34] (SPF). Another

[31] Original data are available for download at https://www.aeaweb.org/articles.php?doi=10.1257/0002828042002651.

[32] http://www.philadelphiafed.org/research-and-data/real-time-center/greenbook-data/pdf-data-set.cfm

[33] http://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/

[34] A similar approach has been followed by Coibion et al. (2012) who use consensus forecasts from

element of discontinuity from the original methodology dates September 2008. Following this date, the intended fed fund rate is specified as an intended range rather than an intended single target; for all those dates which are affected by this change in classification, therefore, we identify the intended target as the mid point of the official intended range. Data relative to the fed fund rate level and target range at each FOMC meeting date for the subperiod 1997-2012 are from Bloomberg. The instrument at quarterly frequency is finally obtained summing up the residuals from equation (D.7) over the observations relative to the meeting dates belonging to each specific quarter.

E BVAR Results

	Horizon					
	0	1	4	8	16	20
USGDP	0	0.4	1.4	4.1	12.3	13.3
EUGDP	0	0.1	1.9	4.4	4.2	6.7
IPROD	0	0.2	0.5	0.3	3.5	7.4
RPCE	0	2.1	1.7	2.7	9.9	11.9
RDPI	0	0.0	0.8	0.4	3.5	4.9
RPFIR	0	0.4	0.3	4.8	12.7	14.4
EMPLY	0	0.3	0.3	0.3	5.1	9.4
HOUST	0	0.2	0.2	1.1	11.7	12.6
CSENT	0	0.3	1.2	1.6	8.0	8.0
GDPDEF	0	1.3	1.8	7.9	19.7	19.6
PCEDEF	0	1.2	4.7	13.5	19.7	19.5
FEDFUNDS	77.8	67.2	42.4	26.5	18.2	14.6
GDC	9.1	7.9	13.1	12.1	11.5	16.0
GCB	8.9	12.9	13.9	7.3	10.0	15.6
GCNB	5.9	4.7	4.5	2.7	8.1	17.0
USBLEV	0.1	2.3	2.8	3.9	5.7	6.3
EUBLEV	1.3	2.0	2.9	2.1	5.0	5.0
USDEUR	1.0	2.8	7.4	7.4	6.5	6.1
USDGBP	1.1	1.5	3.4	4.7	6.5	4.8
MTWO	5.3	13.0	12.0	15.2	8.4	8.4
TSPREAD	44.4	42.5	23.3	14.3	11.2	8.9
EURATE	5.0	8.9	7.2	8.2	5.2	4.3
UKRATE	0.1	0.8	1.7	4.9	3.8	3.5
GRVAR	0.6	1.1	4.2	6.7	9.0	8.1
GFAC	1.3	0.8	1.8	1.7	6.5	8.8
GZEBP	0.0	0.1	3.6	5.3	6.8	6.9

TABLE E.1: Variance Decomposition. The table reports the forecast error variance decomposition in the baseline BVAR(4), for the variables listed in Table 3, when the monetary policy shock is identified under the recursive Cholesky scheme. Forecast horizons, in columns, are expressed in quarters. Shares of variance explained by the monetary innovations are expressed in percentage points.

the Blue Chip Economic Indicators to substitute for Greenbook forecasts in an extension of the RR04 narrative shock which covers the period 1969-2008.

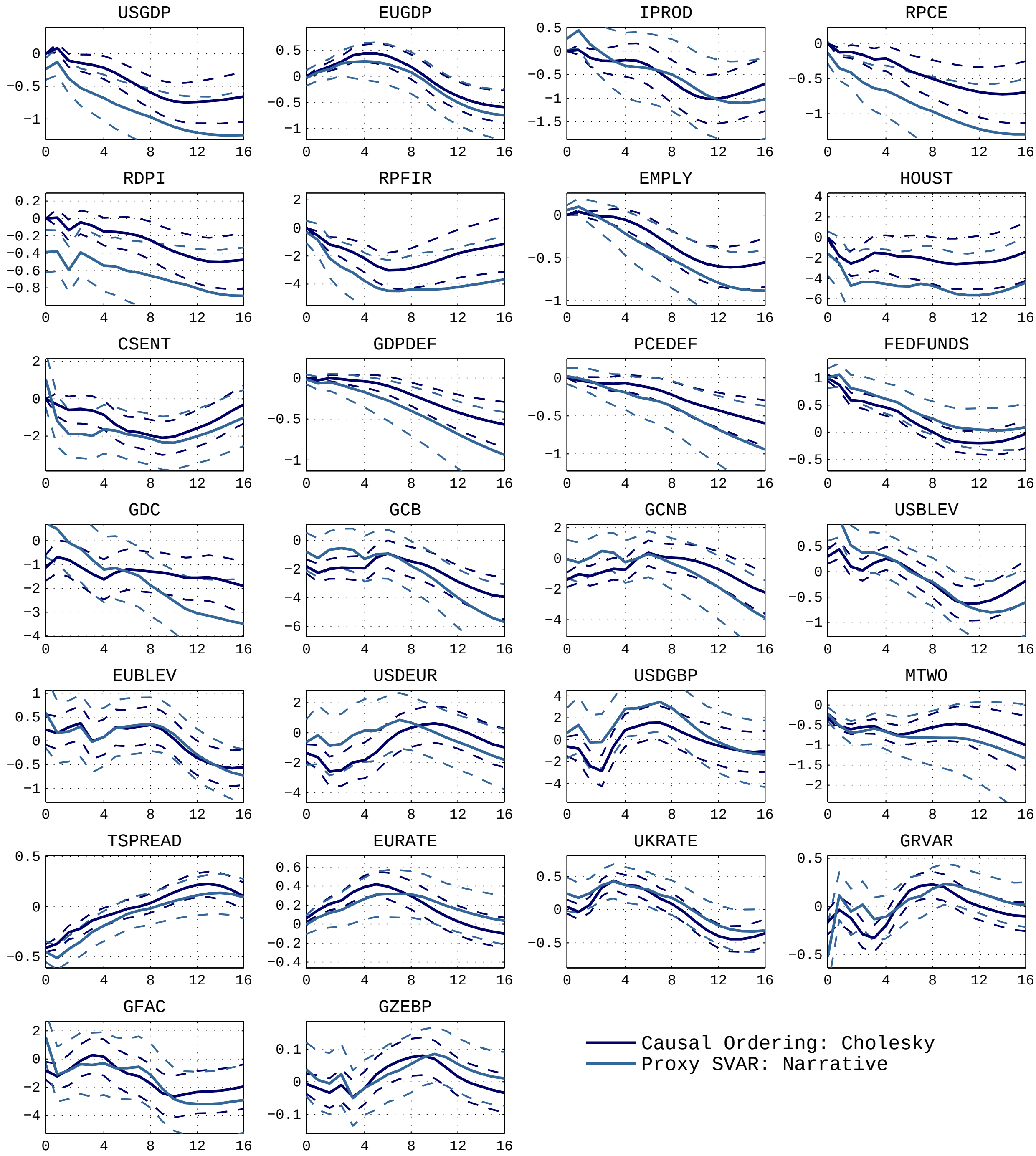

FIGURE E.1: Responses to a monetary policy shock normalized to induce a 100 basis point increase in the EFFR. Baseline specification. The variables included are those listed in Table 3; the estimation sample is 1980Q1 to 2010Q4, the lag order of the BVAR is set to 4. The narrative instrument is built on an underlying set truncated at Dec 2007. The chart compares responses obtained when the monetary policy shock is identified using a recursive scheme (dark blue line) with those resulting from a Proxy SVAR with narrative-based instrument (light blue line). Dotted lines limit the 68% posterior coverage bands.

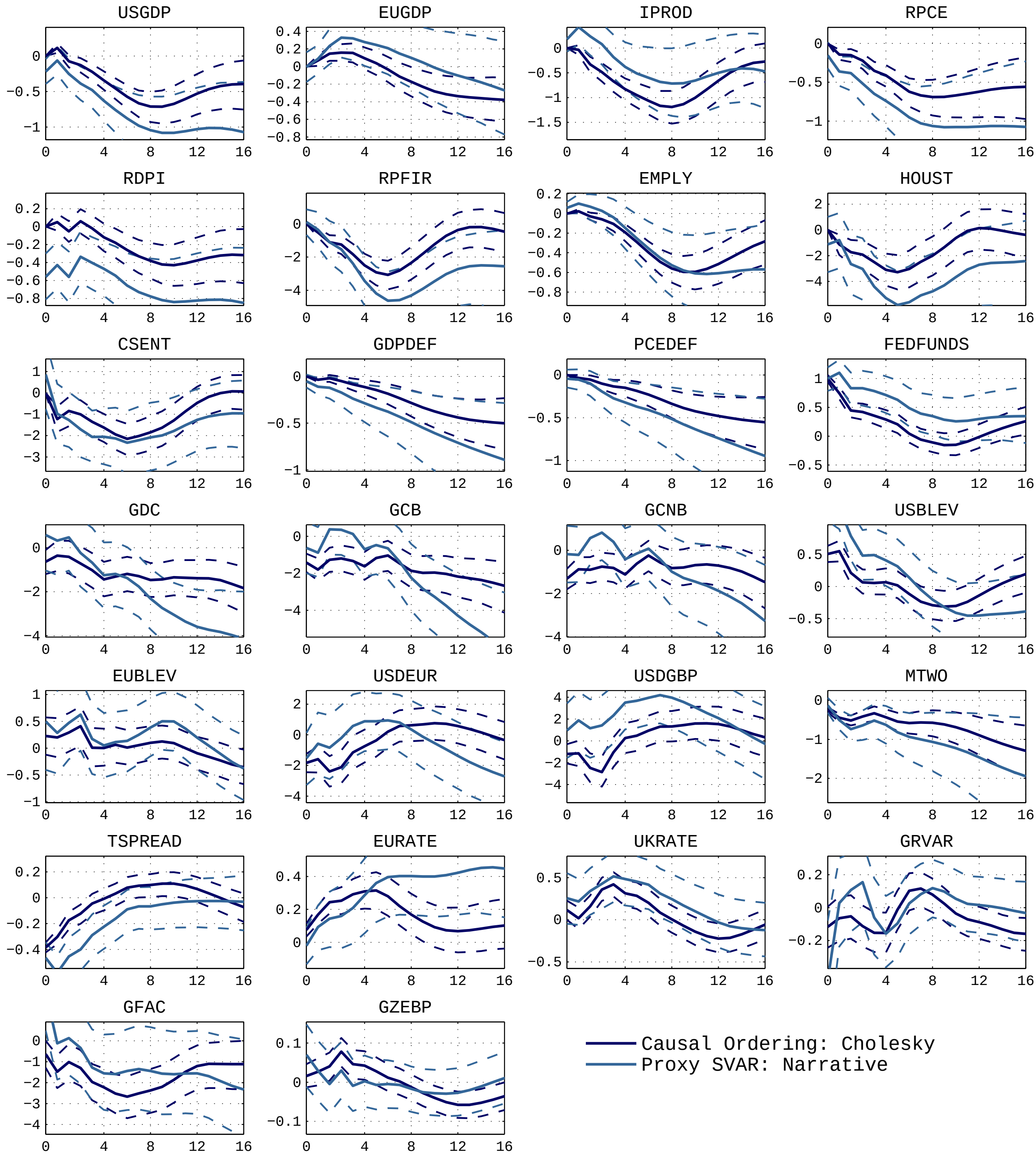

FIGURE E.2: Responses to a monetary policy shock normalized to induce a 100 basis point increase in the EFFR. The variables included are those listed in Table 3; the estimation sample is 1980Q1 to 2010Q4, the lag order of the BVAR is set to 4. The narrative instrument is built on an underlying set truncated at Mar 2009. The chart compares responses obtained when the monetary policy shock is identified using a recursive scheme (dark blue line) with those resulting from a Proxy SVAR with narrative-based instrument (light blue line). Dotted lines limit the 68% posterior coverage bands.

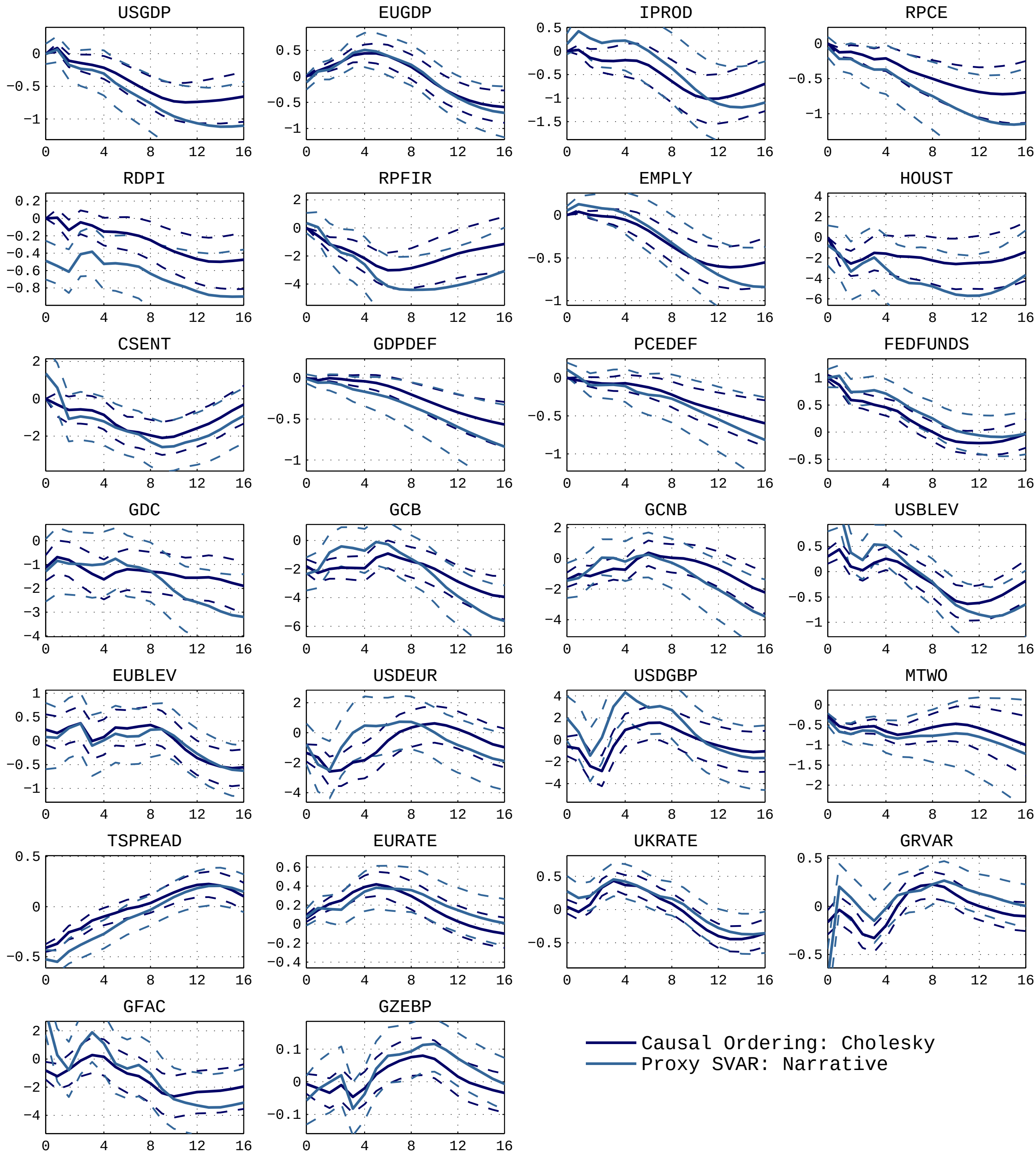

FIGURE E.3: Responses to a monetary policy shock normalized to induce a 100 basis point increase in the EFFR. The variables included are those listed in Table 3; the estimation sample is 1980Q1 to 2007Q2, the lag order of the BVAR is set to 4. The narrative instrument is built on an underlying set truncated at Dec 2007. The chart compares responses obtained when the monetary policy shock is identified using a recursive scheme (dark blue line) with those resulting from a Proxy SVAR with narrative-based instrument (light blue line). Dotted lines limit the 68% posterior coverage bands.

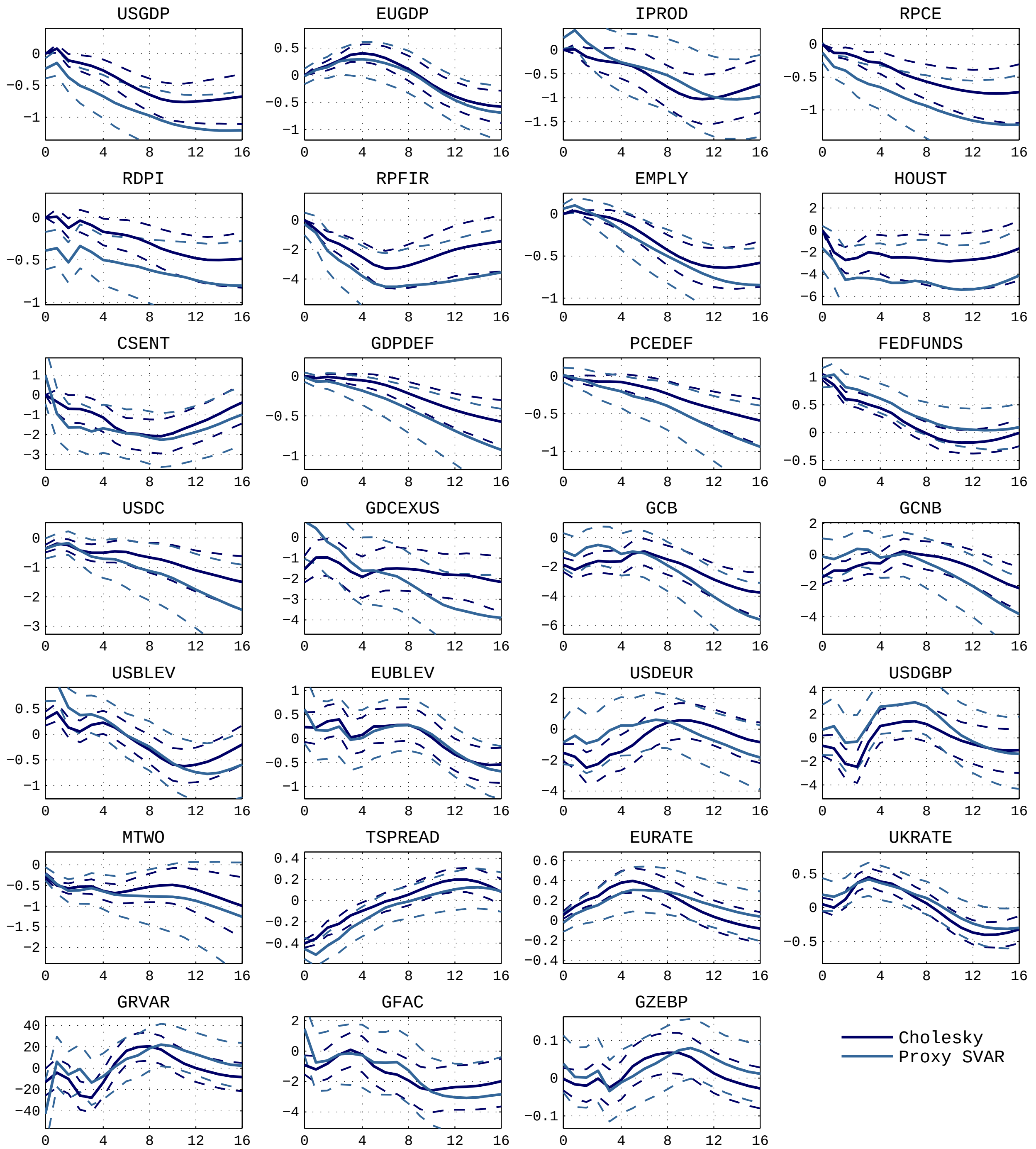

FIGURE E.4: Responses to a monetary policy shock normalized to induce a 100 basis point increase in the EFFR. Global domestic credit in the baseline specification is split between US and rest of the world; the remaining variables are those listed in Table 3; the estimation sample is 1980Q1 to 2010Q4, the lag order of the BVAR is set to 4. The narrative instrument is built on an underlying set truncated at Dec 2007. The chart compares responses obtained when the monetary policy shock is identified using a recursive scheme (dark blue line) with those resulting from a Proxy SVAR with narrative-based instrument (light blue line). Dotted lines limit the 68% posterior coverage bands.

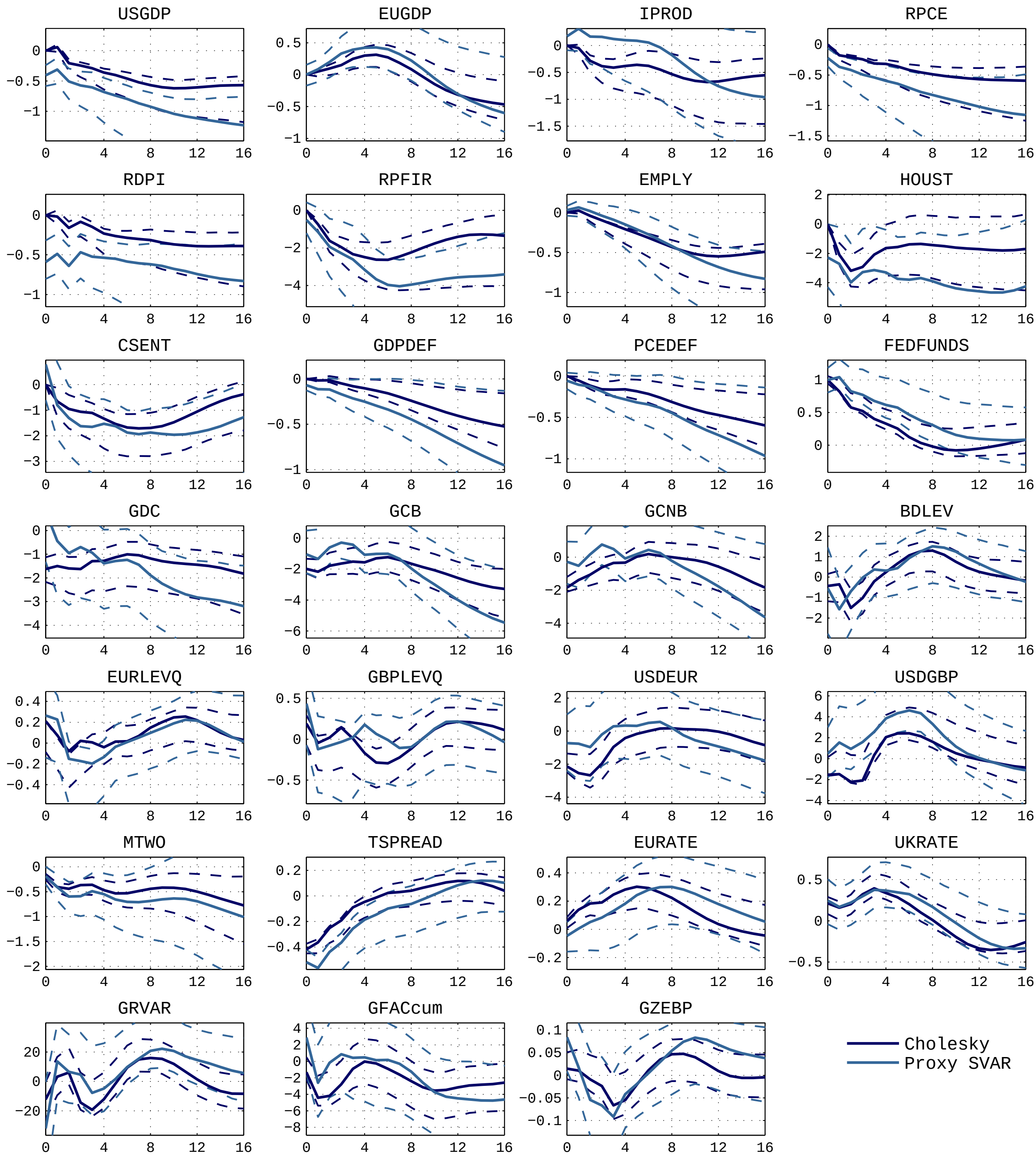

FIGURE E.5: Responses to a monetary policy shock normalized to induce a 100 basis point increase in the EFFR. Banking sector leverage in the baseline specification is replaced with GSIBs leverage ratios; the remaining variables included are those listed in Table 3; the estimation sample is 1980Q1 to 2010Q4, the lag order of the BVAR is set to 4. The narrative instrument is built on an underlying set truncated at Dec 2007. The chart compares responses obtained when the monetary policy shock is identified using a recursive scheme (dark blue line) with those resulting from a Proxy SVAR with narrative-based instrument (light blue line). Dotted lines limit the 68% posterior coverage bands.