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. This global factor can be interpreted as reflecting the time-varying degree of market wide risk aversion and aggregate volatility. Importantly, we show, using a large Bayesian VAR, that US monetary policy is a driver of this global factor in risky asset prices, the term spread and measures of the risk premium. US monetary policy is also a driver of US and European banks leverage, credit growth in the US and abroad and cross-border credit flows. Our large Bayesian VAR allows us to avoid the problem of omitted variables bias and, for the first time, to study in detail the workings of the "global financial cycle", i.e. the interactions between US monetary policy, global financial variables and real activity.

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1 Introduction

Observers of balance of payment statistics and international investment positions all agree: the international financial landscape has undergone massive transformations since the 1990s. Financial globalisation is upon us in a historically unprecedented way - we probably surpassed the former 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 (2006) and, for a recent survey, Gourinchas and Rey (2014)). What has not been explored as much however are the consequences of financial globalisation on 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 for the 1990-2012 period and a guiding theoretical framework, this paper seeks to fill this gap, i.e. to analyse the effect of financial globalisation on the workings of national financial systems around the globe.

The paper main contributions are (i) to document the existence of a "global financial cycle" 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 model with heterogenous investors; (ii) to investigate the effect of US monetary policy on global asset returns, credit growth, leverage and economic activity using a state-of-the-art large Bayesian VAR methodology. We find evidence in favour of a powerful transmission channel of US monetary policy across borders via credit flows, leverage, risk premia and the term spread, emphasizing the need of 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 one regional factor. In other words, returns on stocks and corporate bonds exhibit a high degree of comovement world wide. This global factor reflects both the aggregate volatility of asset markets and the time-varying degree of risk aversion of markets. A simple model suggests that this aggregate risk aversion can be interpreted as reflecting the investment preferences of leveraged global banks with important capital market operations and that of asset managers such as insurance companies or pension funds. Global banks are assumed to be risk neutral (due to implicit bail out guarantees) and to operate under a value at risk constraint while asset managers are risk averse mean variance investors. When global banks are the main investors, aggregate risk aversion is low and risk premia are small. Our estimates show in particular that the aggregate degree of risk aversion on world markets declined continuously from 2003 to 2006 to reach very low levels.

Our second set of findings is that US monetary policy has a significant effect on the leverage of US and European investors (particularly European and UK capital markets banks), on cross border credit flows and on credit growth worldwide. It also has a powerful effect on the global factor, 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 etc. This points towards important effects of US monetary policy on the world financial system and the global financial cycle: US monetary policy contributes to set the tune for credit conditions world wide in terms of volumes and prices.

Because this paper stands at the cross-road between studies on monetary policy transmission, international spillovers via capital flows and role of financial intermediaries, the relevant literature is huge and cannot be comprehensively covered. Our empirical results on flows are consistent with the findings of Fratzscher (2012) who studies the crisis period using high frequency fund data and finds an important role for "push factors" in driving financial flows, of Forbes and Warnock (2012) and of Bruno and Shin (2014), Claessens et al. (2014), who relate aggregate flow data to push factors such as the VIX. This recent literature echoes and extends findings by Calvo, Leiderman and Reinhart (1990). Goldberg and Cetorelli (2012) use microeconomic data to study the role of global banks in transmitting liquidity conditions across borders. [ADD]

Our results on the transmission mechanism of monetary policy via its impact on risk premia and the term spread are consistent with the results of Gertler and Karadi (2014) on the credit channel of monetary policy in the domestic US context. They are also consistent with Bekaert et al (2014) who study the impact of US monetary policy on components of the VIX and with the results of Rey (2013) and Bruno and Shin (2014) who analyse the effect of US monetary policy on leverage and on the VIX. All these studies use small VARs to avoid the curse of dimensionality.

From a theoretical point of view, the paper is related to the work of [ADD: Geanokoplos, Shin, Adrian and Shin, and of Borio (though the concept of financial cycle is different from the BIS one) and to Krishnamurty and He, Brunnermeier Sannikov, Farhi and Werning, Korinek and Jeanne, Stein, Kiyotaki Gertler, Bernanke Gertler etc..] .All these papers have in common an emphasis on models where frictions in the financial sector are key.

From an econometric point of view, we build on te work of Reichnlin Stock Watson for the Dynamic Factor analysis allowing us to decompose fulctuation sin risky asset returns into a global and a regional component. We also build on recent development in the Bayesian VAR literature in Banbura et al (2013) , Lenza et al (2013).

The present paper differs from the literature in that it provides an integrated framework where the existence of a global financial cycle in asset prices is established and analysed and the international dimensions of US monetary policy take centre stage. The use of a large Bayesian VAR allows, we believe for the first time, the integrated analysis of financial, monetary and real variables interactions, in the US and abroad.

We introduce a guiding theoretical framework in Section 2 and show relevant microeconomic data on banks in Section 3. We present estimates of the Dynamic Factor Model in Section 4, as well as a decomposition of the Global Factor. Section 5 performs the Bayesian VAR analysis to study the effect of US monetary policy on real activity and the global financial cycle.

2 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 or pension funds, on the other hand. The model presented in this section is admittedly very simple: it is only there to help us interpret the data in a transparent way, our contribution being first and foremost empirical.

We consider a world in which there are two types of investors: global banks and asset managers. Global banks are leveraged entities which operate on all asset markets and fund themselves in dollars for their operations in capital markets. They can borrow at the US riskless rate. They leverage to buy a portfolio of world risky securities, whose returns are in dollars. Global banks are risk neutral investors in world capital markets and are subject to a Value at Risk constraint, which we assume is imposed to them by regulation. Their risk neutrality is an extreme assumption which maybe 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 too 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 3.

The second type of investors are asset managers, such as insurers or pension funds who, like global banks, acquire world risky securities in world markets and can borrow at the US riskless rate. Asset managers also hold a portfolio of regional assets (for example regional real estate) which is non traded in financial markets, may be because of information asymmetries. Asset managers however are standard mean variance investors and exhibit therefore a positive degree of risk aversion limiting their desire to leverage. The fact that asset managers have a regional portfolio and not the global banks is non essential (global banks could be allowed to hold a portfolio of regional loans for example). The asymmetry in risk aversion (risk neutral banks with value at risk constraint and risk averse asset managers) is however important for the results.

Our framework is related to Danielsson, Shin and Zigrand (2011), Adrian and Shin (2011a) and Etula (2010), Adrian and Boyarenko (2014).

Heterogenous investors : **Global Banks**

Global banks maximize the expected return of their portfolio of world risky assets subject to a Value at Risk constraint (VaR). The VaR imposes an upper limit on the amount a bank is predicted to lose with a certain given probability. The VaR will be taken to be proportional to the volatility 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 tradeable securities such as equities and corporate bonds. We denote by $\mathbf{x}_t^B$ the portfolio weights of a global bank. We call w_t^B the equity of the bank.

A global bank chooses its portfolio such that:

$$\max_{x_t^B} E_t\left(\mathbf{x}_t^{B\prime}\mathbf{R}_{t+1}\right)$$

$$s.t.\ VaR_t \leq w_t^B$$

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

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

Writing the Lagrangian of the maximization problem, taking the first order condition and using the fact that the constraint is binding (since banks are risk neutral) gives the following solution for the vector of asset demands :

$$\mathbf{x}_t^B = \frac{1}{\alpha\lambda_t}\left[Var_t(\mathbf{R}_{t+1})\right]^{-1} E_t(\mathbf{R}_{t+1}) \tag{1}$$

This is formally similar to the portfolio allocation of a mean variance investor. λ_t is the Lagrange multiplier. In this set up the VaR constraint plays the same role as risk aversion.

Heterogenous investors : **Asset Managers**

Asset managers such as insurers and pension funds 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 the 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 (for example real estate). We denote by $\mathbf{y}_t$ the fractions of their wealth invested in those regional assets. The vector of returns on these non tradable investments is $\mathbf{R}_t^N$. Finally, we call w_t^I the wealth of asset managers. An asset manager chooses his portfolio of risky assets by maximizing:

$$\max_{x_t^I} E_t\left(\mathbf{x}_t^{I\prime}\mathbf{R}_{t+1} + \mathbf{y}_t^{I\prime}\mathbf{R}_{t+1}^N\right) - \frac{\sigma}{2} Var_t(\mathbf{x}_t^{I\prime}\mathbf{R}_{t+1} + \mathbf{y}_t^{I\prime}\mathbf{R}_{t+1}^N)$$

Hence the optimal portfolio choice in risky tradable securities for an asset manager will be:

$$\mathbf{x}_t^I = \frac{1}{\sigma}\left[Var_t(\mathbf{R}_{t+1})\right]^{-1}\left[E_t(\mathbf{R}_{t+1}) - \sigma Cov_t(\mathbf{R}_{t+1}, \mathbf{R}_{t+1}^N)\mathbf{y}_t^I\right] \tag{2}$$

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 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

$$E_t\left(\mathbf{R}_{t+1}\right) = [\frac{w_t^B + w_t^I}{\frac{w_t^B}{\alpha\lambda_t} + \frac{w_t^I}{\sigma}}]\left[Var_t(\mathbf{R}_{t+1})\ \mathbf{s}_t + Cov_t(\mathbf{R}_{t+1}, \mathbf{R}_{t+1}^N)\mathbf{y}_t\right]$$

Let us call $[\frac{w_t^B + w_t^I}{\frac{w_t^B}{\alpha\lambda_t} + \frac{w_t^I}{\sigma}}] = \Gamma_t$.

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:

$$E_t\left(\mathbf{R}_{t+1}\right) = \Gamma_t Var_t(\mathbf{R}_{t+1})\ \mathbf{s}_t + \Gamma_t Cov_t(\mathbf{R}_{t+1}, \mathbf{R}_{t+1}^N)\mathbf{y}_t \tag{3}$$

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, it would be equal to σ. The risk premium on risky securities is scaled up by the market effective risk aversion and depends on aggregate volatility and on their comovement with non traded assets (real estate). Therefore excess returns have a global component (aggregate volatility scaled by effective risk aversion) and a regional one.

Global Banks Returns

We can now compute the expected excess return of a global bank portfolio in our economy:

$$\begin{aligned} E_t(\mathbf{x}_t^{B\prime}\mathbf{R}_{t+1}) &= \Gamma_t Cov_t(\mathbf{x}_t^{B\prime}\mathbf{R}_{t+1}, \mathbf{s}_t^{\prime}\mathbf{R}_{t+1}) + \Gamma_t Cov_t(\mathbf{x}_t^{B\prime}\mathbf{R}_{t+1}, \mathbf{y}_t^{\prime}\mathbf{R}_{t+1}^{N}) \\ &= \beta_t^{BW}\Gamma_t \ + \beta_t^{BN}\Gamma_t \end{aligned}$$

where β_t^{BW} is the beta of the global bank with the world market and β_t^{BN} is the beta of the global bank with the non traded regional risk. 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 which loaded most on world risk. The excess return is scaled up by the global degree of risk aversion Γ_t in the economy.

3 Evidence on Global Banks

Within the theoretical framework defined in previous sections, the expected excess return of a global bank portfolio in our economy is equal to: $E_t(\mathbf{x}_t^{B\prime}\mathbf{R}_{t+1}) = \beta_t^{BW}\Gamma_t + \beta_t^{BN}\Gamma_t$ where β_t^{BW} is a measure of risk loading on the world market, β_t^{BN} is a measure of risk loading on the regional market and Γ_t is our effective aggregate risk aversion parameter. To investigate global banks behavior 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. 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 Financial Institutions (*G-SIFIs*). The list of G-SIFIs, 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", has been compiled by the Financial Stability Board together with the Basel Committee of Banking Supervision in November 2011 to isolate global financial services groups that are systemically relevant[1]. A complete list of institutions included in our set is

[1] http://www.financialstabilityboard.org/publications/r_111104bb.pdf

in Table A.4 in Appendix.

Figures 1 reports the correlation between beta and returns calculated over the entire sample and the GSiFi subsample respectively. We use August 2007 as a breaking point to distinguish between pre and post crisis periods.

. Graphs showing positive relation between pre crisis beta and returns.

Figure 1:

Results suggest that global banks have gone before the crisis through a phase in which they were building up leverage and loading up on systemic risk, getting high returns and then reverted abruptly after the crisis. In a context in which global banks are risk neutral and subject to a VaR constraint Adrian and Shin (XX) show that if the constraint binds all the times then banks will adjust their positions depending on the perceived risk so that their VaR does not change; this mechanism implies that even when risk is low - or perceived as such - they will increase their exposure in a way that ensures their probability of default remains unchanged. Using data on quarterly growth rates of both total assets and leverage Adrian and Shin show that in fact banks, and particularly broker-dealers, react to stronger balance sheets in a systematically different way with respect to households and retail banks or asset managers; specifically, they actively manage their leverage by adjusting their demand for assets in a way that makes leverage procyclical or, in other words, increasing in the size of their balance sheets. we find similar results in our international sample of banks.

Graphs showing positive relation of leverage growth and asset growth for capital markets/G SIfis banks only (retail banks not as cyclical)

This positive association between the size of balance sheets and leverage, combined with the evidence of a rather stable level of total equity, creates room for a potential feedback effect that magnifies the consequences of shocks to asset prices. An increase in asset prices strengthens banks balance sheets reducing their leverage; if, as it seems to be the case, banks privilege a strategy that maintains leverage at a fixed level, they will react to the price shock enlarging the size of their balance sheets by increasing their demand for assets; this, in turn, will push asset prices further reinforcing the cycle. Clearly, these forces will go in opposite direction during a downturn.

Global banks through leveraging and deleveraging effectively influence funding conditions for the entire financial system and ultimately for the broader international economy. Depending on their ability and willingness to take on risk, financial institutions can amplify monetary stimuli introduced by central banks. In particular, easier funding or particularly favorable 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 the attitude towards risk of international financial players that, in turn, determines their willingness to provide cross border or foreign currency financing (CGFS 2011 PAPER).

4 Global factor in risky asset returns

In this section we exploit the properties of a panel of heterogeneous risky asset prices to formally address the implications of the model detailed in Section 2. 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 formally linked to the aggregate degree of risk aversion of the market and to volatility. A natural way to empirically identify the components just detailed is to assume that the collection of world asset prices has a factor structure[2]; in particular, we specify the the factor model such that each (log) 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, and which we will interpret as a proxy for aggregate risk aversion.

[2]Stock and Watson (2002a,b); Bai and Ng (2002); Forni et al. (2005) among others

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:

$$p_{i,t} = \mu_i + \Lambda_i F_t + \xi_{i,t} \tag{4}$$

where μ is a vector of N intercepts μ_i, F_t is a $r \times 1$ 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. Prices dynamic is accounted for both at aggregate and individual level; in particular, we explicitly model the dynamic of both the common and the 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[3].

To identify the different elements at play, we impose further structure to the model in equation (4) 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 modeled according to:

$$p_{i,t} = \mu_i + \lambda_{i,g} f_t^g + \lambda_{i,m} f_t^m + \xi_{i,t}. \tag{5}$$

In equation (5) $p_{i,t}$ 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 only loaded by the

[3]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 ML estimator is proven under this type of misspecification in Doz et al. (2006).

series in p_t that belong to the same (geographical or asset class specific) class m, and of a series-specific component. A similar specification has been adopted by Kose; 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. In the context of the model outlined in equation (4), the implementation of the block structure in (5) is achieved by imposing restrictions to the coefficients in Λ such that the loadings relative to all those blocks the price variable $p_{i,t}$ does not belong to are set to zero. Similar kind of restrictions are also imposed on the matrices of coefficients governing the factors' dynamic. A detailed description of the model discussed here is reported in Appendix 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; condition that clearly does not apply to log asset prices as such; it is necessary, therefore, to be able to estimate the model outlined above, to first transform the series in p_t to achieve stationarity, and then recover the factors in (5). To this purpose, let $\tilde{x_t} \equiv \Delta x_t$ denote the first difference for any variable x_t, then consistent estimates of the common factors in F_t can be obtained by cumulating the factors estimated from the stationary, first-differenced model:

$$\tilde{p_t} = \Lambda \tilde{F_t} + \tilde{\xi_t}. \tag{6}$$

In particular, $\hat{F}_t = \sum_{s=1}^{T} \hat{\tilde{F}}_s$ and $\hat{\xi}_t = \sum_{s=1}^{T} \hat{\tilde{\xi}}_s$. 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 formalization, 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 Europe, the US and Japan and stacked to this set are all major commodities price series[4]. All price series are taken at monthly frequency using end of

[4]The set of commodities considered toes not include precious metals.

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 1975 to December 2010. 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 2010, then we keep only those that have continuously been traded during the entire time span in order to produce a balanced panel. The resulting dataset has an overall cross-sectional dimension of $N = 303$. While we prefer having to deal with such a long time window to have a significant history for use in the analysis in the following sections, requiring the indices to be continuously traded for the entire time horizon necessarily limits the width to our final panel and, consequently its heterogeneity. To gauge the extent to which this choice has a significant impact on the resulting estimated global factor, we repeat the extraction on a much shorter set, stating in January 1990, and containing a total of $N = 428$ different asset prices. The differences in the composition of the two sets is reported in Table 1 where we also highlight the block structure estimated in each of the two instances.

Table 1: **Composition of Asset Price Panels**

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

Notes: 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.

In each case we fit to the data a model with one global and one specific 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 the both sets are collected in Table 2. According to the figures shown, the largest eigenvalue alone, in both the time and frequency domain, accounts for more than 60% of the variability in the data; 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.

Table 2: **Number of Factors**

r	% Cov Mat	% Spec Den	Bai Ng (2002)			Onatski
			IC_p1	IC_p2	IC_p3	
			(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) 1990:2010			
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

Notes: 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.

4.1 The global factor

The global factors estimated from the two sets are plotted in Figure 2. Recall from previous sections that the common factors are obtained via cumulation and are therefore consistently estimated only up to a scale and an initial value F_0 that, without loss of generality, we set to be equal to zero. 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

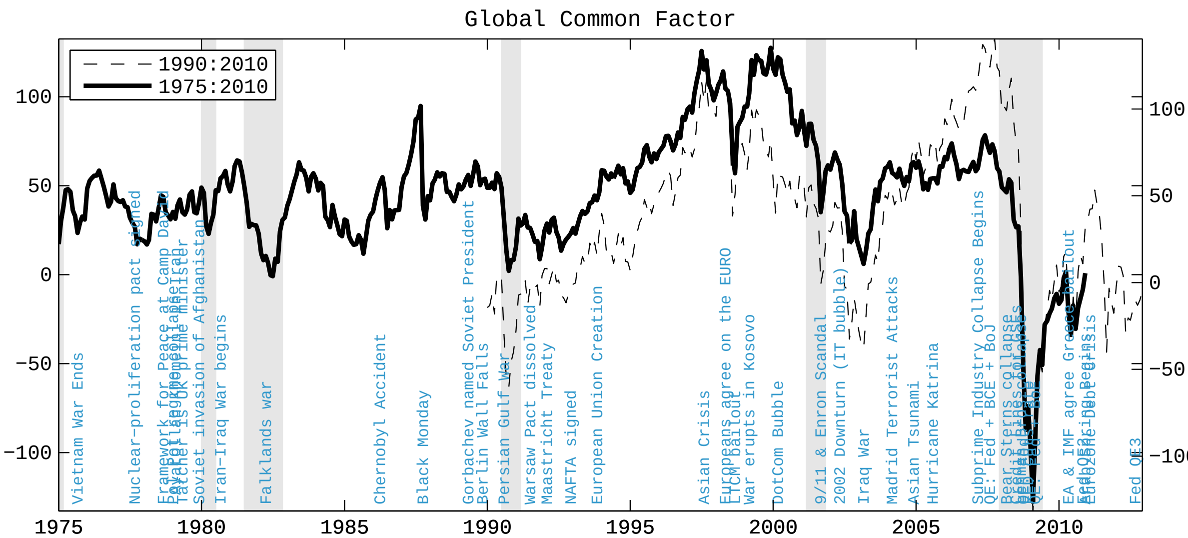

Figure 2: The Figure plots the estimates of the global factor for the 1975:2010 sample (bold line) together with the one estimates on the wider, shorter sample 1990:2010. Text at the bottom of the figure highlights major worldwide events. Shaded areas denote NBER recession dates.

information *per se*; rather, it is the overall shape, the points in time at which it peaks and the turning points that are of interest and deserve particular attention.

Figure 2 shows that the factor is consistent with both the US recession periods as identified by the NBER and highlight major worldwide events which we also report in the chart. The index declines in concomitance with all the recession episodes but remains relatively stable until the beginning of the Nineties when a sharp and sustained increase is recorded which lasts until the end of the decade when a few major events like the LTCM bailout and the East Asian Crisis revert the increasing path that was presumably due, at least in part, to the building up of the *dot-com* bubble. Such 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 the collapse of the subprime market, the first signals of increased vulnerability of the financial markets become visible, leading to an unprecedent decline that has only partially recovered since then. 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

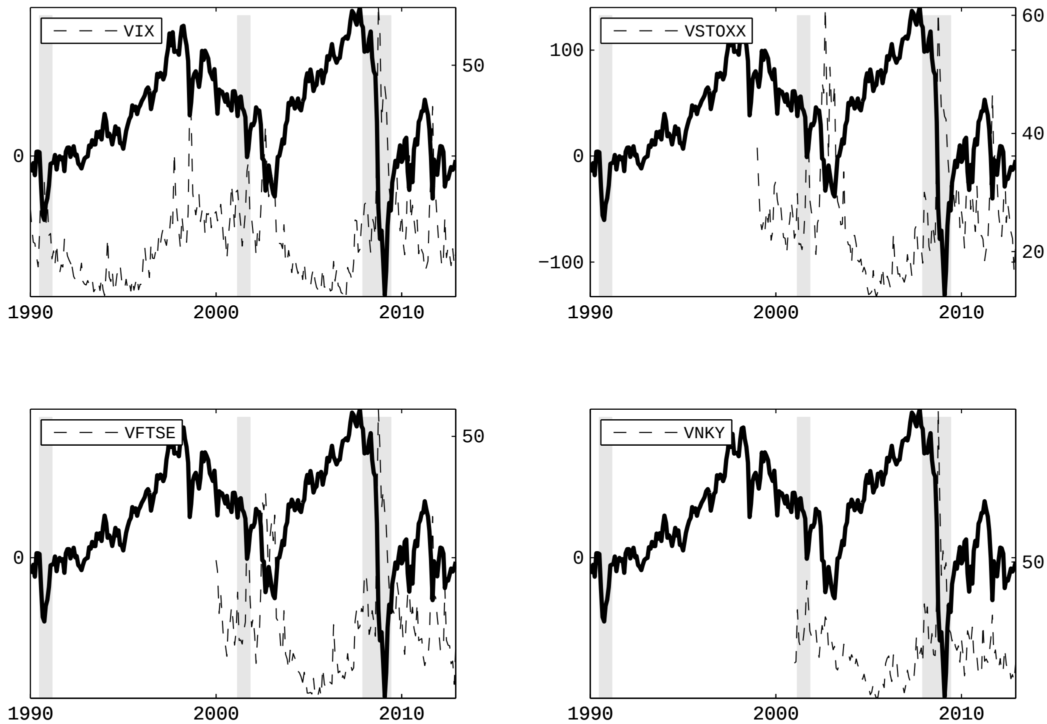

Figure 3: The Figure plots the global factor (bold line) together with major volatility indices (dotted lines); clockwise from top left panel: VIX (US); VSTOXX (EU); VFTSE (UK) and VNKY (JP).

this choice by repeating the same exercise on the same global set (1975:2010) where, instead, we leave the currency in which the assets are originally traded in unchanged. The resulting global factor is very much alike 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; the two global factors are plotted against one another in figure **??** in Appendix **??**. Intuitively, the robustness of the estimate of the global factor with respect to currency transformations comes directly from the structure imposed in (5); looking again at Table 1 it is easy to verify that the blocks roughly coincide with currency areas and that, therefore, this aspect will naturally be captured by the regional factors.

Following the intuition detailed in Section 2, a global factordescribing the evolution of heterogeneous world asset prices can be decomposed into a volatility component and an effective degree of aggregate degree of risk appetite. In Figures 3 and 4 we plot the factor against other indicators which are commonly utilized to measure markets uncertainty and risk aversion; as such, we expect all of them to be inversely related to our factor. In Figure 3 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 UK respectively, and VFKNY for Japan. Volatility indices are explicitly constructed to measure the market's implied volatility and reflect the risk-neutral expectation of future market variance; they are typically regarded as an instrument to assess the degree of strains and risk in the financial market. We note that the factor and the volatility indices display a remarkable common behavior and peaks consistently coincide within the overlapping samples; while the comparison with the VIX is somehow facilitated by the length of the CBOE index, the same considerations easily extend to all other indices analyzed. Finally, Figure 4 compares the factor with the GZ-spread of Gilchrist and Zakrajsek BIB and the Baa-Aaa corporate bond spread; both commonly used as measures of the degree of market stress and default risk. The GZ-spread is a default-free indicator intended to capture investors' expectation about future economic outcomes; it is constructed as a measure of borrowing costs faced by different firms, in particular, as an average of individual spreads themselves constructed as the difference between yield of corporate bonds and a corresponding risk-free security with the same implied cash flow. While, to some degree, the three indices display some commonalities, the synchronicity is less obvious than the one we find with respect to the volatility indices.

For illustrative purposes, we finally explore the possibility of decomposing the global factor such that the global variance component is separated from the rest. To do so we construct a raw measure of realized monthly global volatility using daily returns of the MSCI Index[5]. In standard empirical finance applications daily measures of realized variance are

[5]This approach follows from applications in e.g. Bollerslev, Tauchen and Zhou (2009) BIB where variance

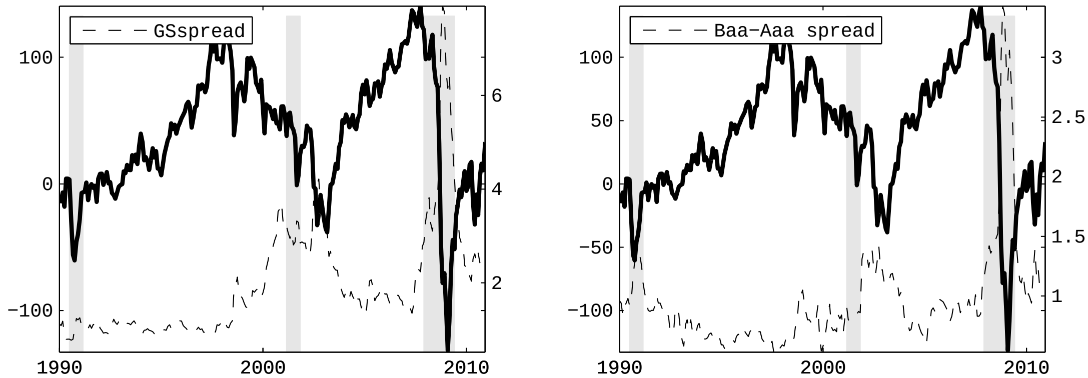

Figure 4: The Figure plots the global factor (bold line) with the GZ spread (left) and the Baa-Aaa Corporate bond spread (right).

typically calculated using the quadratic variation of the returns. This translates in practical terms into summing over intraday squared returns sampled at very high frequency, procedure which is shown to provide a very accurate estimation of the true, unobserved, return variation (Andersen et al 2001a, 2001b, Barndorff-Nielsen&Sheppard 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 daily returns provide a sufficiently accurate proxy of the global realized market variance at monthly frequency. Figure 5 summarizes the results of this exercise; the top panel reports the values of the global realized variance while the inverse of the centered residual of the projection of the global factor on the realized variance is in the bottom panel. The construction of our proxy for aggregate risk aversion is modeled along the lines of Bollerslev 2009 and Bekaert 2011 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 realized variance.Very interestingly the degree of market risk aversion is in continuous decline between 2003 and 2006 to very low levels, at a time where volatility is uniformly low. It then jumps up during the financial crisis.

risk premia are measured as the difference between implied (expectation under risk neutral probability) and realized variances.

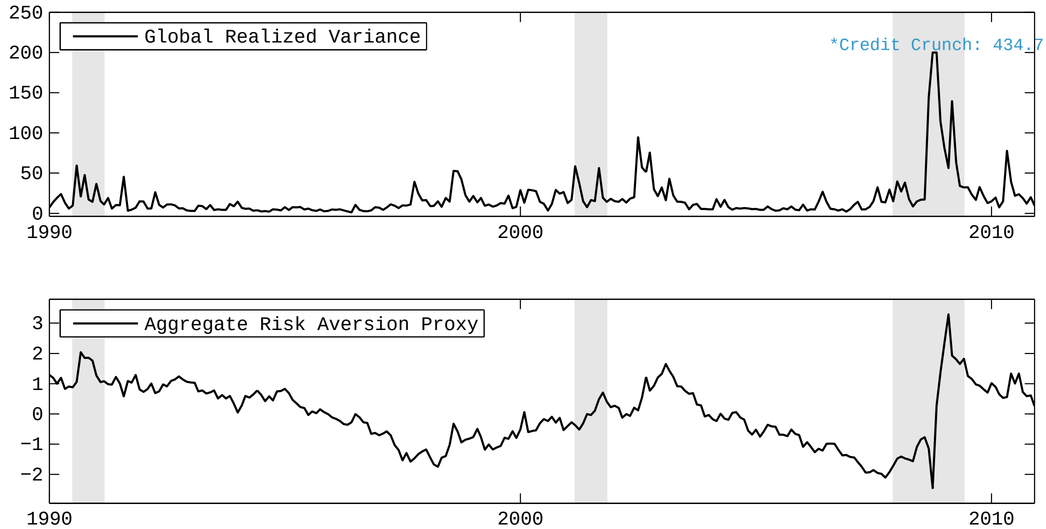

Figure 5: The top panel of the figure reports an index of global realized variance measured using daily returns of the MSCI Index, we limit the axis scale to enhance readability excluding periods referring to the Credit Crunch episode where the index reached a maximum of 434.70. In the bottom panel we plot an index of aggregate risk aversion calculated as (the inverse of) the residual of the projection of the global factor onto the realized variance.

5 Monetary Policy, Risk, Leverage and Their Repercussion.

Short introduction; main points being: (1) global banks fund themselves largely in USD; (2) leverage of global banks depends on their risk aversion (reference to model), is procyclical (reference to bank correls section); (3) banks behavior influences the provision of world credit both domestically and internationally; (4) importance of liquidity availability and capital flows for both financial and real sector and for transmission of monetary policy abroad; (5) due to combination of the above it is hard to discard the presumably central role played by US monetary policy in influencing global banks attitude towards risk, credit conditions, market uncertainty and future outlooks.

We study the interaction between monetary policy, credit and global banks leverage using a large Bayesian VAR where we augment the typical set of macroeconomic variables, including output, inflation, investment and labor data, with our variables of interest. To analyze the risk taking 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 is Bekaert et al 2012 BIB which decompose the VIX index into an uncertainty component which is mainly driven by market variance, and a residual proxy for risk aversion and study the effects of a monetary policy shock on both. 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 fund rate as the monetary policy instrument. They find that lax monetary policy reduces both risk aversion and market uncertainty and find the effect on the former being more significant. In a more recent exercise, Bruno and Shin 2014 BIB put together a four-variable VAR with quarterly data from the end of 1995 to the end of 2007 which features the federal funds target rate as the monetary policy instrument, the leverage ratio of US brokers and dealers as a proxy for global banks leverage, the VIX index and the US dollar real effective exchange rate. They find that contractionary monetary policy, while increasing leverage on impact, induces a following significant decrease at medium horizons and that the VIX responds in a symmetrical way; the effect on the US dollar value is somewhat muted and only becomes significant (negative) after a very long horizon. These results, however, only hold within the selected twelve-years time span. In an additional exercise the same authors find that contractionary monetary policy also leads to a decline in bank-to-bank cross-border capital flows at medium horizons.

While these studies have the undoubtable merit of addressing in a formal way the role played by monetary policy in the context of risk-building and the role of banks leverage in acting as intermediaries of the transmission mechanism of monetary policy through cross-border lending activities, they are nonetheless subject to an important criticism which inevitably affects modeling choices which only involve a very small set of variables in that 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 favor of small-scale systems typically levers on the so called curse of dimensionality; in an unrestricted VAR with n variables, an intercept and p lags, adding one extra variable requires the estimation of $p(2n+1)+1$ additional free parameters and the risks of overparametrization 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 be simply not feasible. Here we address this issue by using a large Bayesian VAR as in Banbura et al BIB where the informativeness of the prior is determined as in Giannone Lenza and Primiceri BIB. Intuitively, the solution to the problem achieved by Bayesian estimation accounts to use informative priors which shrink the richly parametrized unrestricted VAR towards a more parsimonious naive benchmark thus effectively reducing estimation uncertainty. Bayesian forecasts approach optimality provided that the degree of shrinkage (or tightness of the prior distribution) is increasing in the number of variables included in the system[6] (De Mol et al BIB). The variables which we include in the baseline BVAR specification are listed in Table 3 together with transformations applied prior to the estimation and ordering for the identification of the monetary policy shock.

The identifying assumption adopted in what follows is that it takes at least one quarter for the slow-moving variables, such as output and prices, 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 (Christiano, Eichenbaum Evans (1999) BIB)[7]. Results, in the form of IRFs, are obtained estimating a BVAR which includes 4 lags; using 3 and 5 lags leads to virtually identical responses. For a more detailed description of

[6]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 more problematic.

[7]An alternative identification assumption, in the context of a six variables VAR, is adopted in Gertler and Karadi (2013) BIB which use Federal Fund Futures to combine high frequency identification with an instrumental variable identification strategy in the spirit of Merten and Ravn (2013) BIB and Stock and Watson (2012) BIB.

Table 3: **Variables in Baseline BVAR.**

ID	Name	Log	S/F	RW Prior
USGDP	US 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		MPI	
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	•
NEER	Nominal Effective Exchange Rate		F	•
MTWO	M2 Money Stock	•	F	•
TSPREAD	Term Spread		F	•
GRVAR	MSCI Realized Variance Annualized	•	F	
GFAC	Global Factor		F	•
GZEBP	GZ Excess Bond Premium		F	

Notes: 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 in denote slow-moving and fast-moving variables respectively; MPI stands for monetary policy instrument. The last column highlights the variables for which we assume a random walk prior.

the BVAR, estimation and priors utilized the reader is referred to Appendix REF at the end of the paper.

The variables of interest in our analysis can be classified in three main groups. First, we look at global credit provision both domestically and internationally; in both cases, we compute global variables as the cross-sectional sum of country-specific equivalents which are constructed following the instructions detailed in Appendix REF. Global inflows are here intended as direct cross-border credit (Avdjiev, McCauley McGuire (2012)) BIB provided by foreign banks to both banks and non-banks in the recipient country. Second, we look at banks leverage. In this respect, following the differences highlighted in Section REF, we distinguish between the banking sector as a whole (baseline specification) and globally systemic US and European banks[8]. Finally, we analyze 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 (summarized by the global price factor estimated in Section REF), financial markets uncertainty (proxied by the index of global realized market variance described in Section REF), the term spread (calculated as the spread between the 10-year and 1-year constant maturity Treasury rates) and the GZ excess bond premium (Gilchrist and Zakrajšek (2012) BIB). Following Gertler and Karadi (2013) BIB, we measure credit costs using both the term premia and credit spreads; while in a world with frictionless financial markets, for given maturity, the return on private securities equals that on government bonds and effects on the yield curve translate directly into changes in the borrowing rates, active frictions might additionally create room for a credit channel in which strict monetary policy not only lowers borrowing rates, but also increases the external finance premium - defined as the spread between private and government securities - due to tightening of financial constraints. Responses of these variables to a monetary policy shock are in Figures (6) to (**??**); the IRFs are normalized such that a contractionary monetary policy shock corresponds to a 100 basis points increase in the Effective Federal Funds Rate[9].

Table 4 reports the forecast error variance decomposition for a selection of the variables included in the BVAR[10]. At a first glance, the percentages shown might be interpreted as being relatively small, however, considering the number of variables included in the system, the size of the monetary policy shock which results from the figures displayed shouldn't be at all surprising. The assessment of the systematic component of monetary policy depends on the conditioning information set used in the analysis, reason for which 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 miss-specification errors; once,

[8]Details on the construction of aggregated banking sector leverage are in Appendix REF at the end of the paper.

[9]A complete set of impulse response functions for all the variables included in the BVAR (Table 3) are in Appendix REF.

[10]Variance decomposition for the full list is reported in Table REF in Appendix REF.

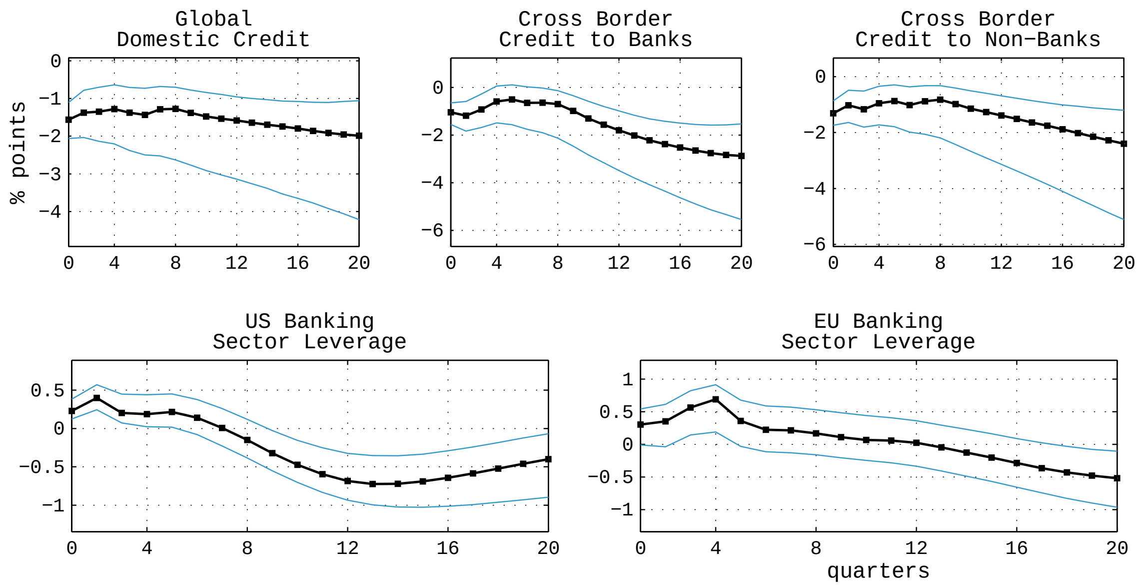

Figure 6: Response of global domestic and international credit (top row) and of banking sector leverage (bottom row) to a monetary policy shock inducing a 100 basis point increase in the EFFR. Light blue lines limit the 68% posterior coverage bands.

Table 4: **Variance Decomposition: Selected Variables.**

	Horizon					
	0	1	4	8	16	20
USGDP	0	0.7	1.0	1.8	5.7	5.7
EMPLY	0	0.4	0.9	1.0	7.0	7.0
GDPDEF	0	0.0	0.1	0.1	0.6	0.3
FEDFUNDS	76.1	67.7	44.2	30.7	15.9	12.5
GDC	4.7	5.0	4.5	5.8	6.7	6.1
GCB	2.5	3.0	2.1	1.3	1.2	0.9
GCNB	2.9	2.1	1.8	1.9	2.7	2.4
USBLEV	3.7	6.5	7.0	4.7	8.0	8.5
EUBLEV	0.8	0.5	3.2	3.3	4.1	4.3
TSPREAD	43.6	41.2	24.9	16.6	11.9	10.7
GRVAR	1.8	2.7	3.6	4.8	5.6	6.0
GFAC	1.6	0.9	4.7	3.5	4.5	5.4
GZEBP	0.2	1.9	4.0	7.6	8.2	7.9

Notes: The table reports the forecast error variance decomposition in the baseline BVAR for a selection of the variables listed in Table 3. Values are expressed in percentage.

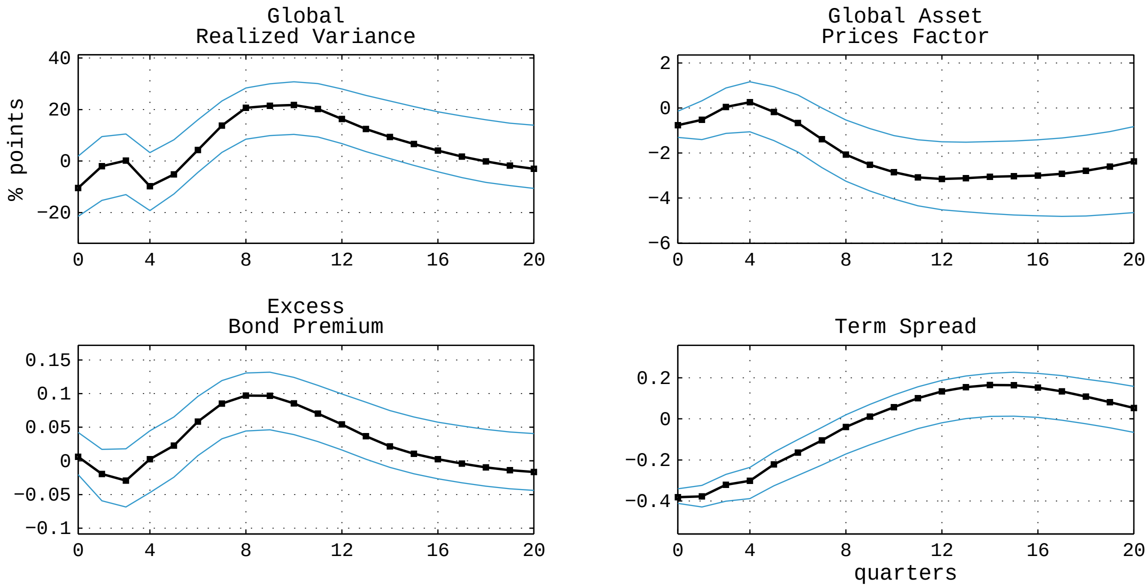

Figure 7: The figure highlights the role of monetary policy in the context of risk building, financial stability and credit costs. Clockwise from top left panel the plots report responses of global realized market variance, the global asset prices factor, the GZ excess bond premium and the term spread to a monetary policy shock inducing a 100 basis point increase in the EFFR. Light blue lines limit the 68% posterior coverage bands.

on the other hand, more realistic scenarios are involved in terms of conditioning information set, then the size of the unsystematic component of monetary policy is consequently resized (Banbura et al. BIB). That said, we still find that monetary policy explains a non trivial fraction of the forecast error variance of banks leverage, credit costs and financial markets-related variables.

6 Discussion and Conclusion

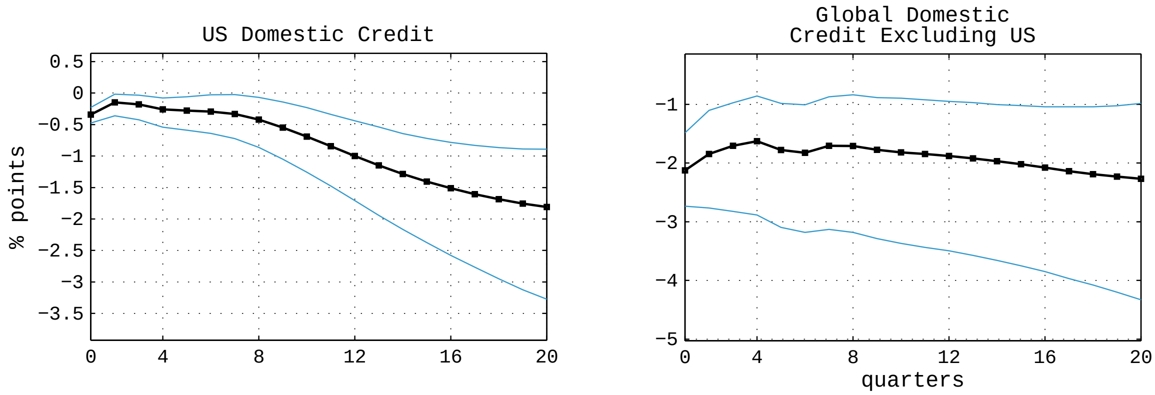

Figure 8: Response of global credit variables to a monetary policy shock inducing a 100 basis point increase in the EFFR. Detail on US versus ROW domestic credit measures. Light blue lines limit the 68% posterior coverage bands.

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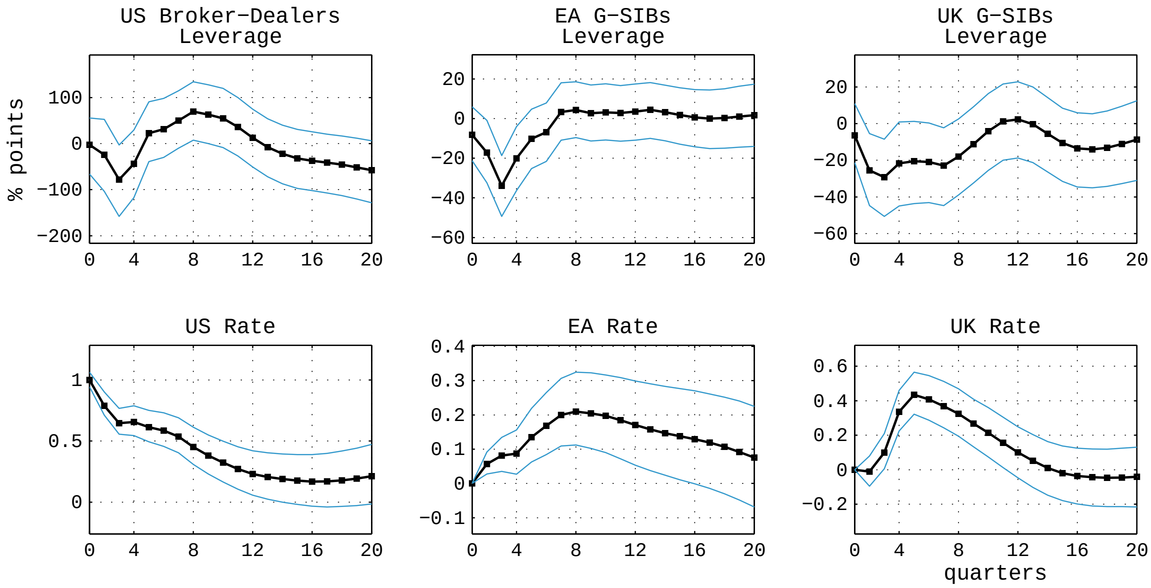

Figure 9: Response of global banks leverage to a monetary policy shock inducing a 100 basis point increase in the EFFR. Light blue lines limit the 68% posterior coverage bands.

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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.

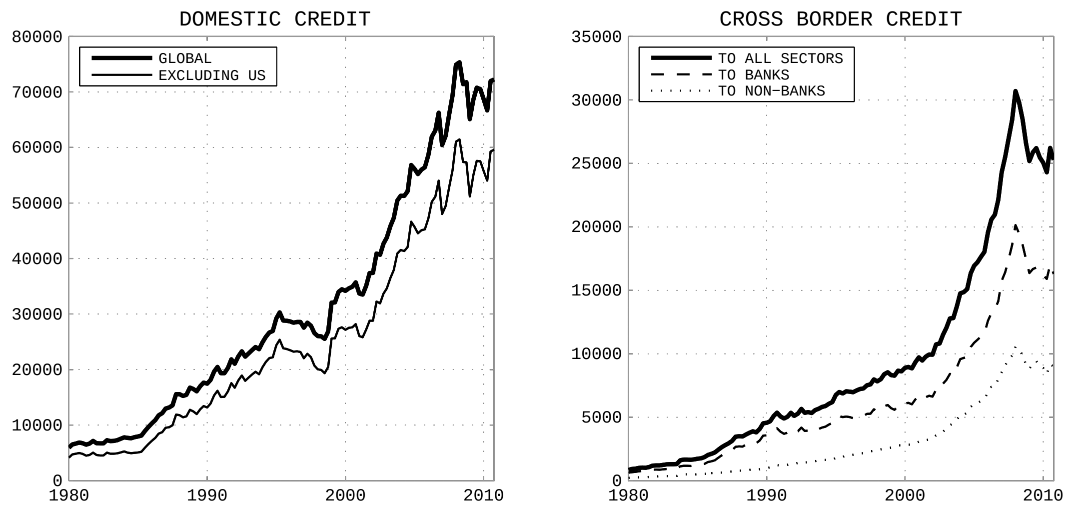

Figure A.1: The Figure plots Global Domestic Credit and Global Cross-Border Inflows constructed as the cross sectional sum of country-specific credit variables. The unit in both plots is Billion USD.

Following Gourinchas and Obstfeld (2012) INSERT REFERENCE 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

Table A.1: **List of Countries Included**

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

Notes: 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.

there exists a discontinuity between data available under the old and new classifications we interpolate the missing observations. Global Domestic Credit is finally constructed as the cross-sectional sum of the National Domestic Credit variables.

To construct the Cross-Border Capital Inflows measures used within the paper we adopt the definition of Direct Cross-Border Credit in INSERT REFERENCE of BIS PAPER use original data available at the BIS Locational Banking Statistics Database and collected under External Positions of Reporting Banks vis-à-vis Individual Countries (Table 6). Data refer to the outstanding amount of Claims to All Sectors and Claims to Non-Bank Sector in all currencies, all instruments, declared by all BIS reporting countries with counterparty location being the individual countries in Table A.1. We then construct Claims to the

Banking Sector as the difference between the two categories available. Original data are available at quarterly frequency in Million USD. Global Inflows are finally calculated as the cross-sectional sum of the national variables. Global domestic credit and global cross-border capital inflows are plotted in Figure A.1.

A.2 Banking Sector and Individual Banks Leverage data

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

The aggregate Leverage Ratios 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 Capitalization (WC08001) downloaded from the same source. Details on the banks included and their characteristics are summarized in Table A.2 below. The aggregated banking sector leverage and the leverage ratio of the European GSIBs are plotted in Figure A.2.

The charts in Section REFERENCE TO SECTION 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,

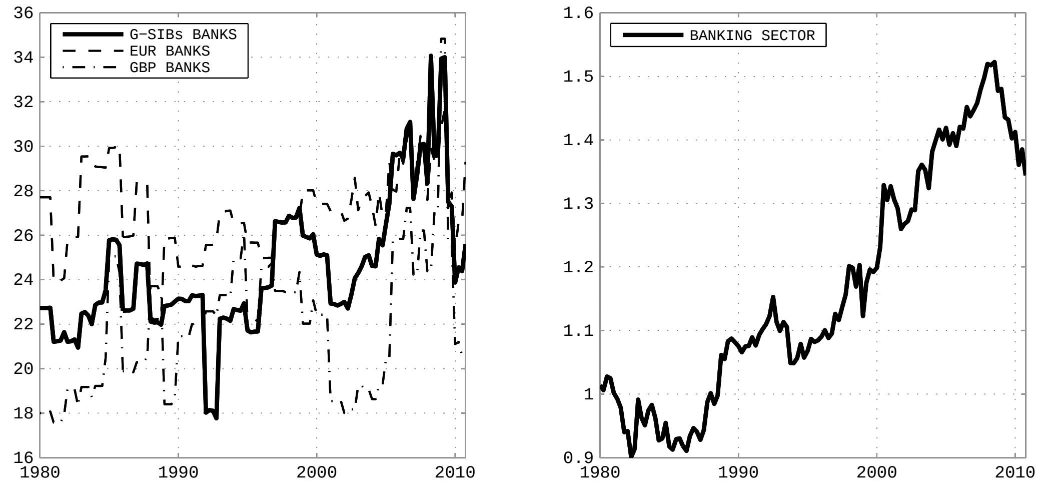

Figure A.2: The left panel plots the leverage ratio calculated for the European GSIBs with a detail on EUR and GBP banks using the institutions and classification in Table A.2. The right panel plots the aggregated European banking sector leverage ratio measured as the median of European countries banking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

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.

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	

continues on next page –

Table A.4 – continued from previous page

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

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Table A.4 – continued from previous page

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

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Table A.4 – continued from previous page

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

Table A.2: **European G-SIBs**

NAME	ISIN	GICS INDUSTRY	COUNTRY	EA LEV	UK LEV
BNP Paribas	FR0000131104	Commercial Banks	France	•	
Crdit 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		•

Notes: 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.

Table A.3: **Bank Data Summary Statistics**

(a)

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

(b)

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

Notes: 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.

B Dynamic Factor Model

Let y_t denote a collection of N stationary demeaned variables such that $y_t = [y_{1,t}, \ldots, y_{N,t}]'$; 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 ($F_t = [f_{1,t}, \ldots, f_{r,t}]'$) that capture systematic sources of variation in the data and are loaded via the coefficients in Λ. Conevrsely, ξ_t is a $N \times 1$ vector of idiosyncratic shocks $\xi_{i,t}$ that capture series-specific variability or measurement errors; we allow elements in ξ_t to display some degree of autocorrelation while we rule out pairwise correlation between assets assuming that all the co-variation is accounted for by the common component. Both the common factors and the idiosyncratic terms are assumed to be zero mean processes.

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

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

where the autoregressive coefficients are collected in the p matrices $\Phi_1, \ldots, \Phi_p$, each of which is $r \times r$; the error term ε_t is a normally distributed zero mean process with covariance matrix Q. Any residual autocorrelation is 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 $E(e_{i,t}, e_{j,s}) = 0$ 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, following Banbura et al. (2010) 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 $(i, \dots, p)$ 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. (2006); Banbura et al. (2010); Engle and Watson (1981); Reis and Watson (2010))[11]. 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[12]. In our empirical application the number of lags in the factors VAR (p) is set to be equal to 1.

[11]Doz et al. (2006) 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.

[12]Forni et al. (2005); Bai and Ng (2002); Stock and Watson (2002a,b) among others.

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):

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

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 $\mathbb{E}(u_t u_t') = Q$. 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 (1986a), Kadiyala and Karlsson (1997), Sims and Zha (1998), Doan Litterman and Sims (1984), Sims (1993) ADD BIB ITEMS.

Litterman (1986a) 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:

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

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. Further, 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 ADD BIB ITEM, however, the residual VAR variance is assumed to be diagonal, option which impairs structural analysis. To overcome this incompatibility Kadiyala and Karlsson (1997) ADD BIB ITEM 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. Further, 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 Litterman and Sims (1984) ADD BIB ITEM 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 ($i = 1, \dots, p$). 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 Banbura et al ADD BIB ITEM. 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 (year) ADD BIB ITEM. To this purpose, rewrite the model in (C.1) as follows:

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

where $\mathrm{Y} \equiv [Y_1, \dots, Y_T]'$ is $[T \times n]$, $\mathrm{X} = [X_1, \dots, X_T]'$ is $[T \times (np+1)]$ with $X_t \equiv [Y'_{t-1}, \dots, Y'_{t-p}, 1]'$,

$U \equiv [u_1, \ldots, u_T]'$ and $\mathbf{B} \equiv [A_1, \ldots, A_p, C]'$ 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:

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

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, Literman and Sims (1984) and the modification introduced by Sims (1993) to allow for cointegration (Coin) are instead implemented adding the following two blocks respectively:

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

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

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, Lenza and Primiceri ADD BIB ITEM 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, Lenza and Primiceri ADD BIB ITEM 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, Lenza and Primiceri ADD BIB ITEM 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 Additional Material

Table D.5: **Variance Decomposition**

	Horizon					
	0	1	4	8	16	20
USGDP	0	0.7	1.0	1.8	5.7	5.7
IPROD	0	0.0	0.5	1.2	7.3	8.4
RPCE	0	0.4	0.3	1.1	3.1	2.7
RDPI	0	0.0	0.1	0.5	1.6	1.3
RPFIR	0	0.2	0.3	4.6	7.3	7.3
EMPLY	0	0.4	0.9	1.0	7.0	7.0
HOUST	0	0.0	0.3	1.9	4.8	4.7
CSENT	0	0.3	0.5	4.0	6.2	5.9
GDPDEF	0	0.0	0.1	0.1	0.6	0.3
PCEDEF	0	0.0	0.3	0.4	0.9	0.5
FEDFUNDS	76.1	67.7	44.2	30.7	15.9	12.5
GDC	4.7	5.0	4.5	5.8	6.7	6.1
GCB	2.5	3.0	2.1	1.3	1.2	0.9
GCNB	2.9	2.1	1.8	1.9	2.7	2.4
USBLEV	3.7	6.5	7.0	4.7	8.0	8.5
EUBLEV	0.8	0.5	3.2	3.3	4.1	4.3
NEER	1.8	1.4	1.1	2.9	4.1	4.0
MTWO	4.4	6.6	5.5	2.1	2.1	2.3
TSPREAD	43.6	41.2	24.9	16.6	11.9	10.7
GRVAR	1.8	2.7	3.6	4.8	5.6	6.0
GFAC	1.6	0.9	4.7	3.5	4.5	5.4
GZEBP	0.2	1.9	4.0	7.6	8.2	7.9

Notes: The table reports the forecast error variance decomposition in the baseline BVAR for the variables listed in Table 3. Values are expressed in percentage.

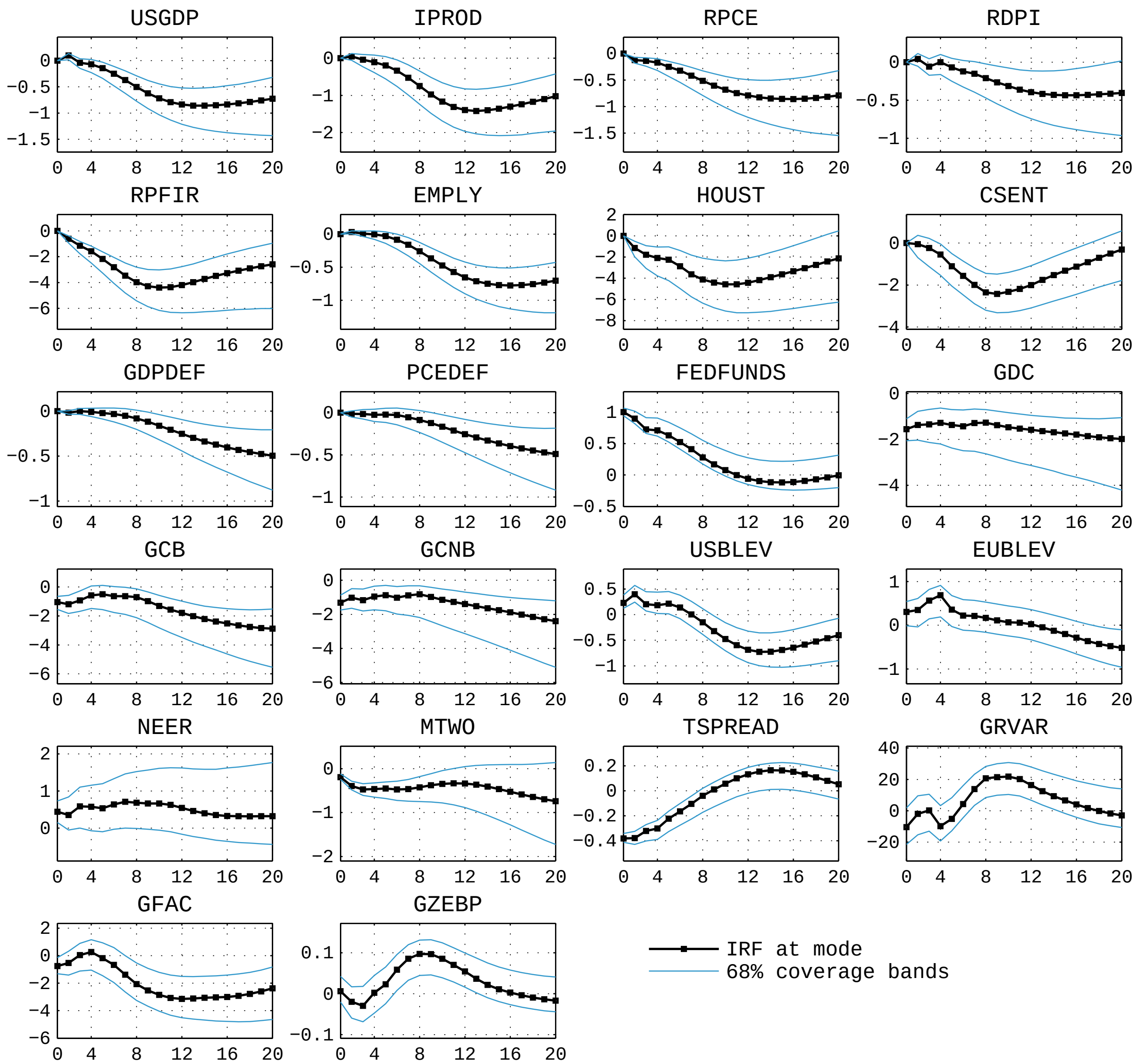

Figure D.3: Responses of variables included in the baseline BVAR specification (Table REF in Section REF) to a monetary policy shock inducing a 100 basis point increase in the EFFR. Light blue lines limit the 68% posterior coverage bands.