US Monetary Policy and the Global Financial Cycle

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International Financial Spillovers of the Hegemon

- What are the consequences of financial globalization on the workings of national financial systems?
- What determines fluctuations in risky asset prices, cross border credit flows, credit growth and leverage in a financially integrated world economy?
- How does the monetary policy of the hegemon affect the Global Financial Cycle ?

Global Financial Cycle

- Document existence of one global factor in risky asset prices in main financial markets around the world (DFM).
- Study joint dynamics of US business cycle and of global financial variables using an information-rich BVAR.
- Identify the role of US Monetary Policy as a driver of the Global Financial Cycle: credit, leverage, risk premium, capital flows, volatility.
- Role of time varying risk aversion interpreted as fluctuations in leverage of global banks in transmitting financial conditions around the world (illustrative model)

Related Literature

- DFM: Doz, Giannone and Reichlin (2006), Bai and Ng (2004), Stock and Watson (2002), Forni et al. (2005)
- Monetary policy VARs: Bekaert et al. (2012), Gertler and Karadi (2015), Banbura et al. (2013), Lenza et al. (2013), Dedola et al. (2015), Ramey (2016), Gerko and Rey (2017), Miranda-Agrippino (2017)
- Monetary policy transmission: Gertler and Kiyotaki (2014), Farhi and Werning (2014, 2015), Curdia and Woodford (2009), Aoki et al. (2015), Coimbra and Rey (2016)
- Role of global banks, capital flows, credit: Bruno and Shin (2014), Fratzscher (2012), Schularick and Taylor (2012), Rey (2013), Forbes and Warnock (2014), Bernanke (2017), Cetorelli and Goldberg (2009), Morais et al (2016), Baskaya et al. (2017).
- Hegemon: Gourinchas and Rey (2007, 2010), Maggiori (2016), Farhi and Maggiori (2017), Gopinath and Stein (2017)

Dynamic Factor Model for Risky Assets

- We estimate a Dynamic Factor Model from a collection of world risky asset returns:

return (i,t) = global factor (t) + regional factors (t)+idiosyncratic (i,t)

- Each return series is the sum of three components:

$$y_{i,t} = \mu_i + \lambda_{i,g} f_t^g + \lambda_{i,m} f_t^m + \xi_{i,t}. \tag{1}$$

1. a global factor that is a common to *all* series in the set
2. a region (or market) specific component common to many but not all series
3. an idiosyncratic asset-specific component

DFM for Risky Assets: Data

- The model is applied to a vast collection of monthly prices of different risky assets traded on all the major global markets:

Table: **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.

DFM for Risky Assets: Model

- Let y_t be an $[N \times 1]$ vector collecting all returns series y_{it}, where x_{it} denotes the return of asset i at time t
- Assume that y_t has a factor structure [Stock and Watson (2002), Bai and Ng (2002), Forni et al. (2005)]

$$y_t = \mu + \Lambda f_t + \xi_t, \tag{2}$$

where μ is constant, f_t is a $[r \times 1]$ vector of zero-mean r common factors loaded via the coefficients in Λ.

- ξ_t is a $[N \times 1]$ vector of idiosyncratic shocks that capture asset-specific variability or measurement errors.

DFM for Risky Assets: Block Structure

- Let the variables in y_t being univocally assigned to one of the nB postulated blocks.
- Order them accordingly such that $y_t = [y_t^1, y_t^2, \ldots, y_t^{nB}]'$; then:

$$y_t = \underbrace{\begin{pmatrix} \Lambda_{1,g} & \Lambda_{1,1} & 0 & \cdots & 0 \\ \Lambda_{2,g} & 0 & \Lambda_{2,2} & & \vdots \\ \vdots & \vdots & & \ddots & 0 \\ \Lambda_{nB,g} & 0 & \cdots & 0 & \Lambda_{nB,nB} \end{pmatrix}}_{\Lambda} \underbrace{\begin{pmatrix} f_t^g \\ f_t^1 \\ f_t^2 \\ \vdots \\ f_t^{nB} \end{pmatrix}}_{f_t} + \xi_t.$$

DFM for Risky Assets: Specification and Estimation

Table: **Number of Factors**

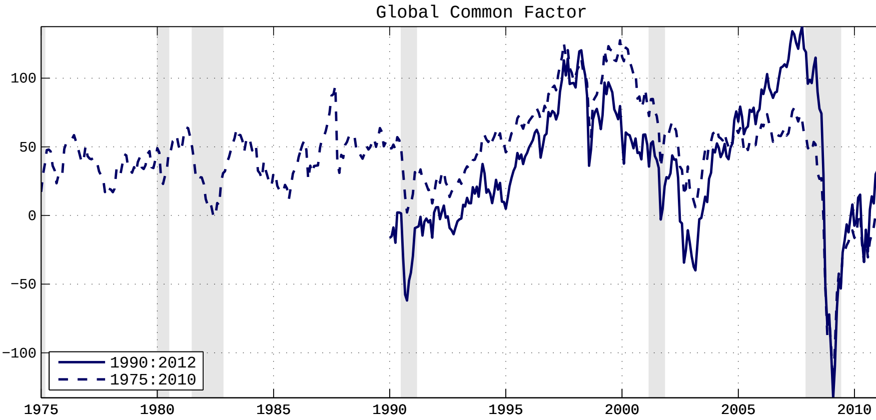
r	% Cov Mat	% Spec Den	Bai Ng (2002)			Onatski
			IC_p1	IC_p2	IC_p3	
			(a) 1975:2010			
1	0.662	0.579	-0.207	-0.204	-0.217	0.015
2	0.117	0.112	-0.179	-0.173	-0.198	0.349
3	0.085	0.075	-0.150	-0.142	-0.179	0.360
4	0.028	0.033	-0.121	-0.110	-0.160	0.658
5	0.020	0.024	-0.093	-0.079	-0.142	0.195
			(b) 1990:2012			
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

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, 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.

Global Financial Cycle and Risky Asset Prices

- Large panel of risky returns around the world.
- We test for the number of global factors.
- The data cannot reject the existence of one and only one global factor. That single factor explains about a quarter of the variance of the data.

Global Factor for World Asset Prices.



RegionalFactors LocalCurrency

Global Factor and Implicit Volatility Indices

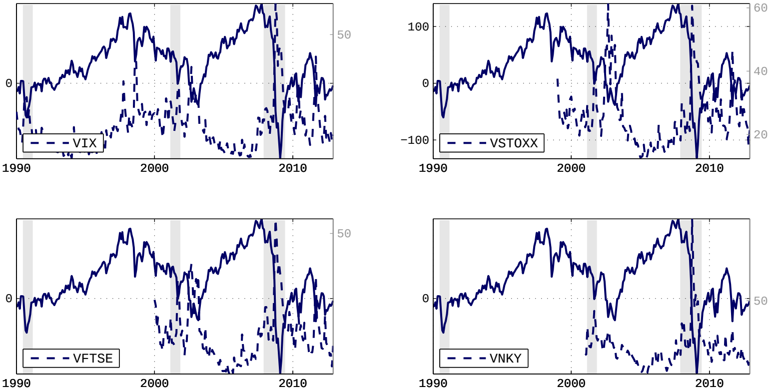


Figure: Global Factor (bold line) and major volatility indices (dotted lines); clockwise from top left panel: US; EU; JP and UK. *Source:* Datastream, authors calculations.

Global Factor Decomposition

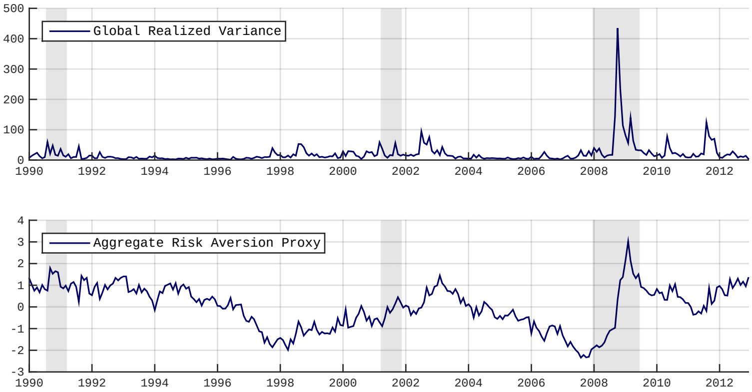


Figure: Decomposition of the global factor in a volatility component and a risk aversion component; the measure of realized monthly global variance is computed using daily returns of the MSCI world index. [Bollerslev et al. (2009)] *Source:* Datastream, authors calculations.

Global Factor Decomposition - Robustness

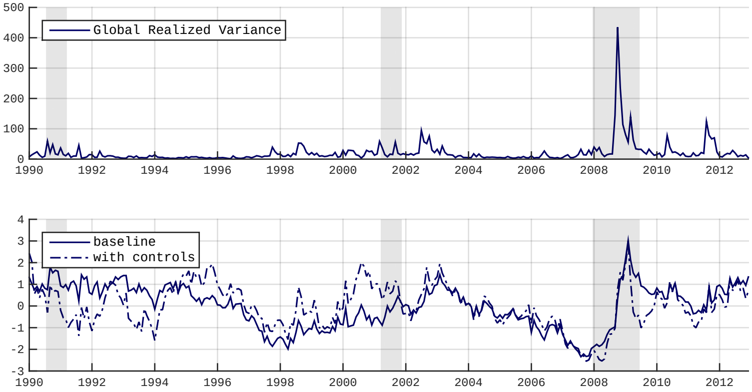
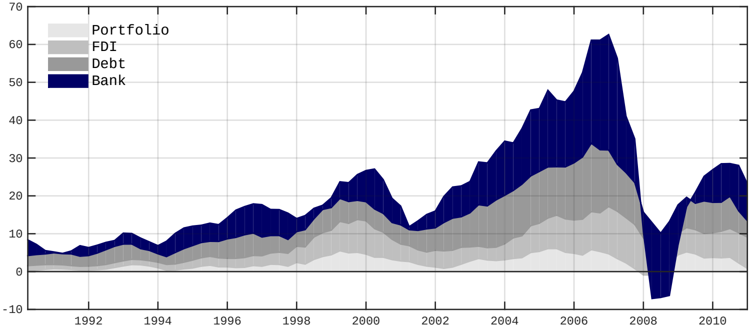


Figure: Decomposition of the global factor in a volatility component and a risk aversion component; controls:discount rates and expected growth rates. *Source:* Datastream, authors calculations.

Global Banks in Cross-Border Flows



leverage credit

US Monetary Policy and the Global Financial Cycle

- How does the monetary policy of the hegemon affect the Global Financial Cycle?

- Role of monetary policy in the center country in setting credit conditions worldwide.

- How does US monetary policy relate to global banks' risk taking behavior?

▸ Data

US Monetary Policy and the Global Financial Cycle

- First paper to estimate the joint dynamics of a large set of real variables and international financial variables.

- Bayesian VAR (in levels) monthly data: typical set of business cycle variables including industrial production, inflation, global real activity with our variables of interest: global credit, cross border flows, financial leverage, global asset prices, risk aversion, credit spreads, exchange rate)

- Identification of monetary policy shocks: high frequency approach (Gurkaynack et al (2005)).

SVAR DetailsOnPriors

US Domestic Business and Financial Cycles 1980-2010

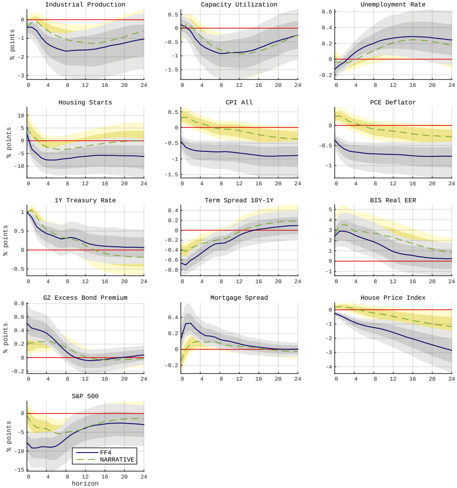


Figure: Response of Business and Financial Cycles (% points) to a monetary policy shock inducing a 100bp increase in the 1 year treasury

Global Financial Cycle–All countries– 1980-2010

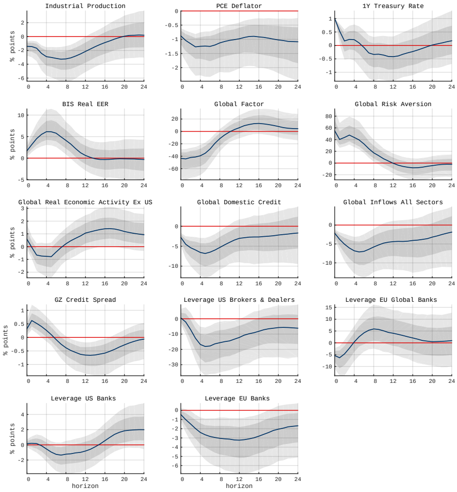


Figure: Response of Business and Financial Cycles (% points) to a monetary policy shock inducing a 100bp increase in the 1 year treasury

Global Financial Cycle– All countries–1990-2010

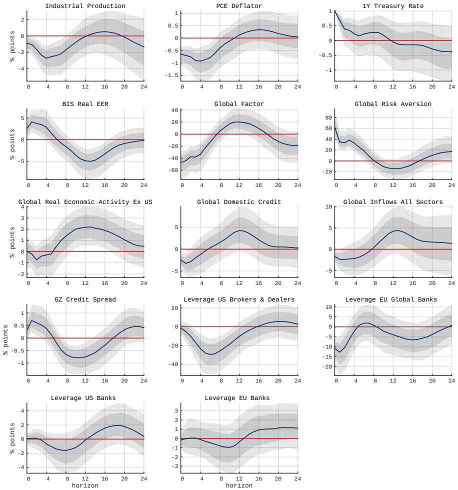


Figure: Response of Business and Financial Cycles (% points) to a monetary policy shock inducing a 100bp increase in the 1 year treasury

Global Financial Cycle– Floaters– 1980-2010

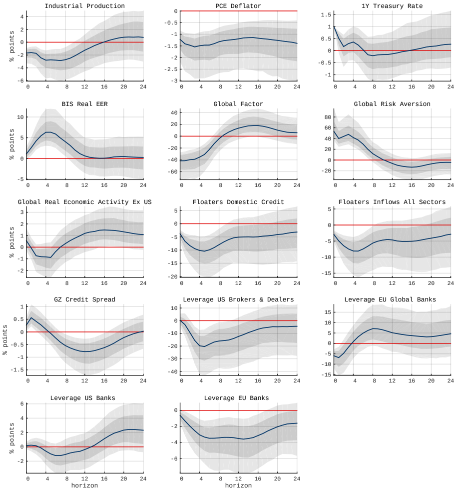
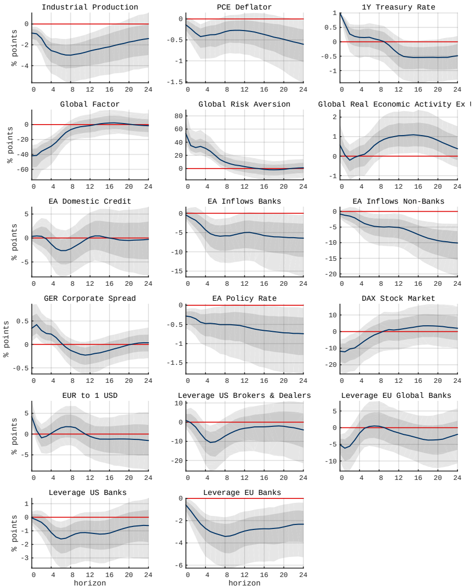


Figure: Response of Business Cycle and Financial Cycles (% points) to a monetary policy shock inducing a 100bp increase in the 1 year treasury

Global Financial Cycle- Euro area– 1980-2010



Global Financial Cycle– UK and Germany– 1980-2010

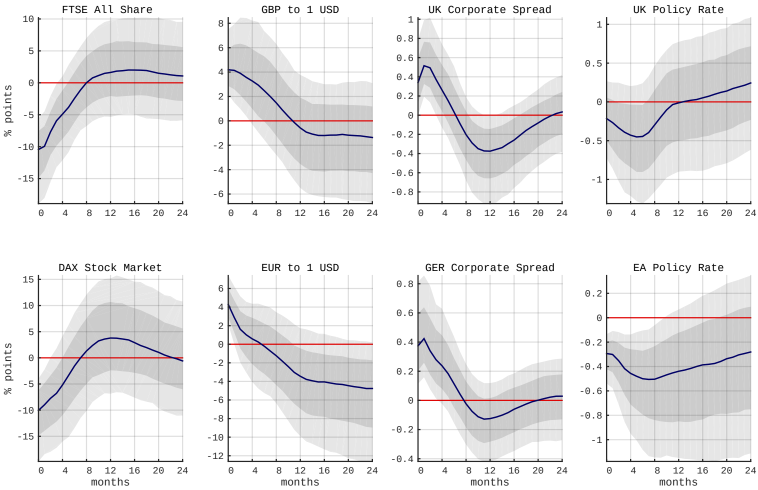


Figure: Response of UK and Germany (% points) to a monetary policy shock inducing a 100bp increase in the 1 year treasury rate.

Global Credit and Cross Border Credit

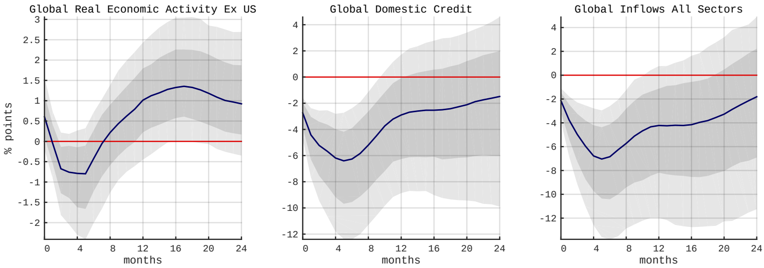


Figure: Response of Global Credit (% points) to a monetary policy shock inducing a 100bp increase in the Effective Fed Funds Rate.

Global Credit and Cross Border Credit (Banks)

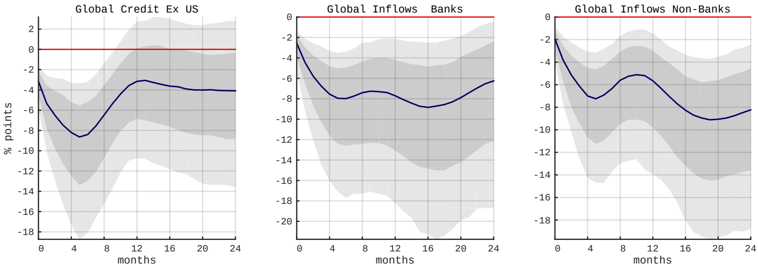


Figure: Response of Global Credit (% points) to a monetary policy shock inducing a 100bp increase in the Effective Fed Funds Rate.

Global Credit and Cross Border Credit (Floaters)

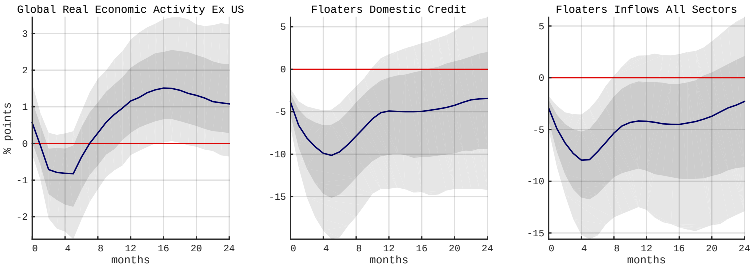


Figure: Response of Global Credit (% points) to a monetary policy shock inducing a 100bp increase in the Effective Fed Funds Rate.

Global Asset Prices and Risk Aversion

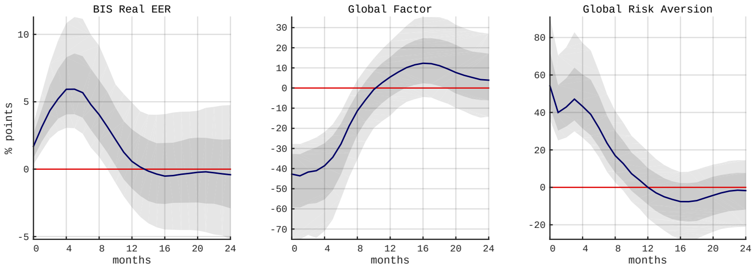


Figure: Response of Asset Prices (% points) to a monetary policy shock inducing a 100bp increase in the Effective Fed Funds Rate.

Other Measures of Risk Aversion

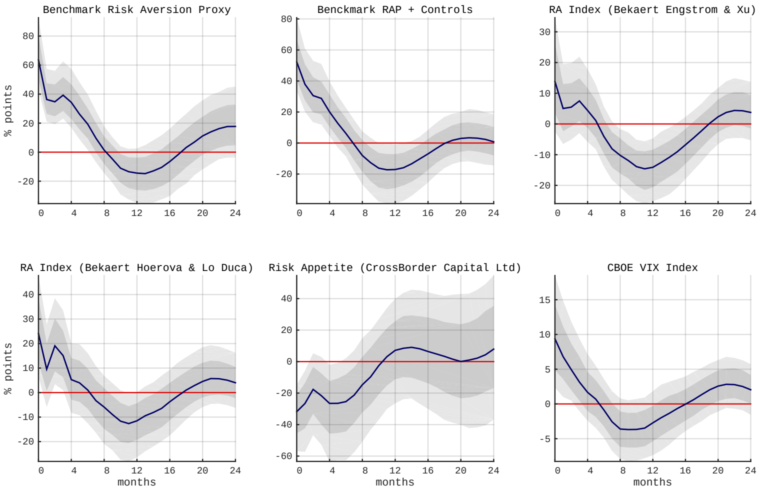


Figure: Response of Risk aversion (% points) to a monetary policy shock inducing a 100bp increase in the Effective Fed Funds Rate.

Bank Leverage in the US and the EU

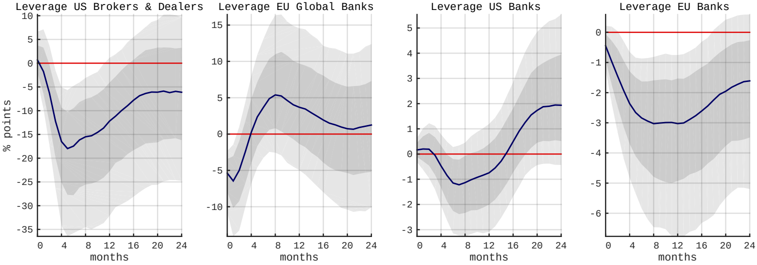


Figure: Response of Banking Sector Leverage (% points) to a monetary policy shock inducing a 100bp increase in the Effective Fed Funds Rate.

Taking stock

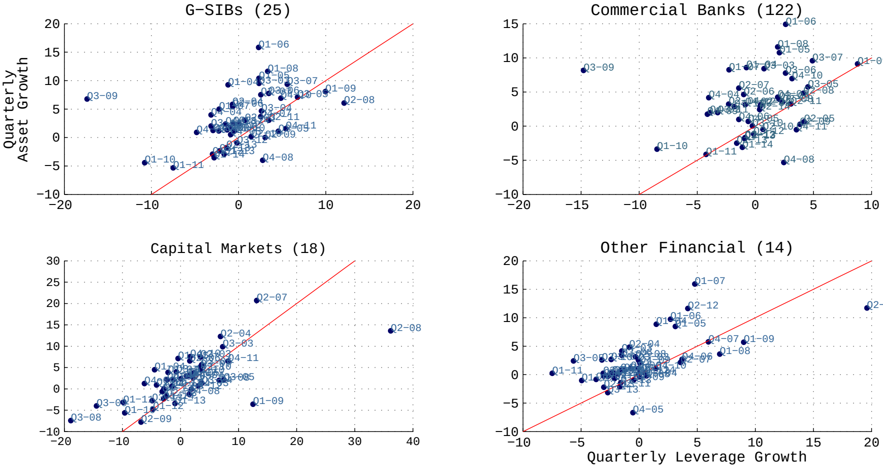
- Important role of one global factor in risky asset prices

- US Monetary Policy is a driver of credit creation worldwide, global factor in asset prices, risk premium, leverage of global banks, cross border credit flows.

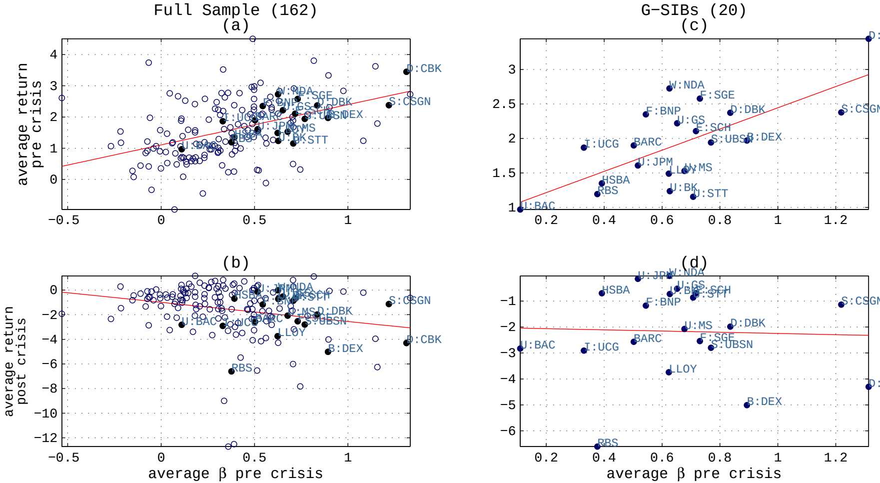
- Interpretation:
  - Stylized model of a globalized world economy where time varying risk aversion is driven by changing importance of leveraged global banks (risk takers)

  - Looser US monetary policy decrease funding costs of global banks who leverage more. When leveraged global banks are marginal pricers of assets, risk premia are lower.

Leverage of Banks



Banks and the Global Factor



A Simple Model of Heterogeneous Financial Intermediaries

- Global Banks

- Asset Managers

A Simple Model of Heterogeneous Financial Intermediaries

- Global Banks
  - operate in world capital markets
  - are risk neutral
  - maximize the expected return of their portfolio of traded world risky assets (securities) subject to a VaR constraint
- Asset Managers

A Simple Model of Heterogeneous Financial Intermediaries

- Global Banks
  - operate in world capital markets
  - are risk neutral
  - maximize the expected return of their portfolio of traded world risky assets (securities) subject to a VaR constraint
- Asset Managers
  - insurers or pension funds
  - are risk averse
  - invest in world traded assets (securities) as well as in regional assets (i.e. regional real estate)

Risk Neutral VaR-constrained Global Banks

- Global banks maximize the expected return of their portfolio of integrated world risky assets subject to a Value at Risk constraint:

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

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

where the VaR_t is defined as a multiple α of the standard deviation of the bank portfolio

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

Risk Neutral VaR-constrained Global Banks

- The vector of asset demands for global banks is given by:

$$\mathbf{x}_t^B = \frac{1}{\alpha\lambda_t}\left[\mathbb{V}_t(\mathbf{R}_{t+1})\right]^{-1}\mathbb{E}_t(\mathbf{R}_{t+1}). \tag{3}$$

- The VaR constraint plays a role similar to risk aversion; λ_t is the lagrange multiplier of the constraint.

Risk Averse Mean-Variance Investors

- Mean variance investors problem:

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

- resulting optimal portfolio choice in risky tradable securities:

$$\mathbf{x}_t^I = \frac{1}{\sigma} \left[\mathbb{V}_t (\mathbf{R}_{t+1}) \right]^{-1} \left[\mathbb{E}_t (\mathbf{R}_{t+1}) - \sigma cov_t (\mathbf{R}_{t+1}, \mathbf{R}_{t+1}^{NT}) \mathbf{y}_t^I \right] \quad (4)$$

Time varying effective risk aversion of the market

- The market clearing condition for risky assets 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 the world vector of net asset supplies for traded assets.

- It follows that:

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

  where $\Gamma_t \equiv \frac{w_t^B + w_t^I}{\frac{w_t^B}{k\lambda_t} + \frac{w_t^I}{\sigma}}$ is the aggregate degree of "effective risk aversion" of the market.

Risky asset excess returns

- Our simple model of international capital markets thus implies that:

$$\mathbb{E}_t\left(\mathbf{R}_{t+1}\right) = \underbrace{\Gamma_t\left[\mathbb{V}_t(\mathbf{R}_{t+1})\right]\mathbf{s}_t}_{\text{Global Factor}} + \underbrace{\Gamma_t cov_t(\mathbf{R}_{t+1}, \mathbf{R}^{NT}_{t+1})\mathbf{y}_t}_{\text{Regional Factor}}$$

- The global factor in risky asset excess returns depends on the wealth-weighted average of the "risk aversion" parameters of the global banks and the asset managers Γ_t and on aggregate uncertainty $\mathbb{V}_t(\mathbf{R}_{t+1})$.
- The larger the banks in the economy compared to other financial players, the smaller the degree of risk aversion (Great Moderation period).

Conclusions

- One global factor explains an important part of the variance of a large cross section of returns of risky assets around the world.
- Information rich Bayesian VAR allows us to study in detail the workings of the "global financial cycle", i.e. the interactions between US monetary policy and global financial variables.
- US monetary policy is a driver of the Global Financial Cycle
- Implications for theoretical modelling of monetary policy transmission and risk taking channel (see Coimbra Rey (2017)).
- Thank you!

The VAR setting (1)

- 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):

$$Y_t = C + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + u_t \tag{5}$$

  where 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 $\mathbb{E}(u_t u_t') = Q$.

- To take full advantage of the large information set without incurring into the curse of dimensionality we estimate the model imposing prior beliefs on the parameters.

The VAR setting (2)

- Provided that the degree of overall shrinkage (i.e. tightness of the prior distribution) is optimally set such that it increases with model complexity, it is possible to increase the cross-sectional dimension of the VAR effectively avoiding overfitting. [De Mol, Giannone and Reichlin (2008)]

- The tightness of the prior in our case is chosen by treating the hyperpriors that govern the prior distribution as additional model parameters. [Giannone, Lenza and Primiceri (2012)]

The VAR setting (3)

- In typical Bayesian applications a prior distribution is specified on the model parameters θ. This distribution depends on a set of hyperparameters γ: $p_\gamma(\theta)$.

- the prior distribution is then combined with the data likelihood $p(Y|\theta)$ and the parameters are estimated as the maximizers of the posterior $p(\theta|Y)$

- typically the hyperparameters γ are chosen following some heuristic criteria (i.e. values that guarantee a certain in-sample fit/out-of-sample forecasting accuracy)

- Here we treat the hyperparameters γ as additional model parameters and estimate them maximizing the marginal data likelihood $p(Y|\gamma)$ [Giannone, Lenza and Primiceri (2012)]

The VAR setting (4)

- We set the following (standard) priors for the coefficients of the VAR: [Banbura, Giannone and Reichlin (2010); Giannone, Lenza and Primiceri (2012); Bloor and Matheson (2008); Auer (2014)]
  - Normal-Inverse Wishart prior [Litterman (1986); Kadyiala and Karlsson (1997)] as a modification of the Minnesota prior to allow for structural analysis.
  - Sum of Coefficients prior [Doan, Litterman and Sims (1984)] allowing for cointegration [Sims (1993)]

The VAR setting (5)

- The Normal-Inverse Wishart prior is a modification of the Minnesota prior which centers all variables in the system around a random walk with drift
- Further characteristics of this prior concern treatment of lags:
  - more distant lags are likely to be less informative than more recent ones
  - lags of other variables are likely to be less informative than own lags
- The priors are implemented using artificial observations in the spirit of Theil mixed estimation.

The NIW prior (1)

- It is a modification of the Minnesota prior [Litterman (1986)] which allows for cross-correlation in the VAR residuals, crucial for structural analysis. [Kadyiala and Karlsson (1997)]
- Given a VAR(p) for the n endogenous variables in $Y_t = [y_{1t}, \ldots, y_{Nt}]'$ of the form:

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

the Minnesota prior assumes

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

- This requires shrinking A_1 towards $eye(n)$ and all other A_i matrices $(i = 2, \ldots, p)$ towards zero.
- Problem: $\mathbb{E}(u_t u_t') = diag(Q)$!

The NIW prior (2)

- The NIW solution:

$$\Sigma \sim \mathcal{W}^{-1}(\Psi, \nu) \qquad \beta|\Sigma \sim \mathcal{N}(b, \Sigma \otimes \Omega),$$

  where β is a vector collecting *all* VAR parameters.
- $\nu = n + 2$ ensures the mean of $\mathcal{W}^{-1}$ exists.
- $\Psi = diag(\psi_i)$ is a function of the residual variance of $AR(p)$ $\forall y_i \in Y_t$.
- Other parameters are chosen to match:

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

- $\lambda = 0$ maximum shrinkage; posterior equals prior.

Implementation of NIW prior

- The NIW prior is implemented adding artificial observations [Theil (1963)] to the stacked version of the VAR:

$$\mathrm{Y} = \mathrm{X}\mathbf{B} + \mathrm{U},$$

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

- Dummy observations:

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

- $J_p \equiv diag(1, \ldots, p)$ and ϵ is a very small number.

Additional Priors (1)

- Sum-of-Coefficients prior (SoC) [Doan, Literman and Sims (1984)]:
  - No-change forecast at the beginning of the sample is a good forecast;
  - Reduces importance of initial observations conditioning on which the estimation is conducted;
  - It is implemented adding *n* artificial observations:

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

- $\overline{Y}$ 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 $\mu \to \infty$ the prior is uninformative.

Additional Priors (2)

- Modification to sum-of-coefficients prior to allow for cointegration (Coin) [Sims (1993)]:
  - No-change forecast *for all variables* at the beginning of the sample is a good forecast;
  - It is implemented adding 1 artificial observation:

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

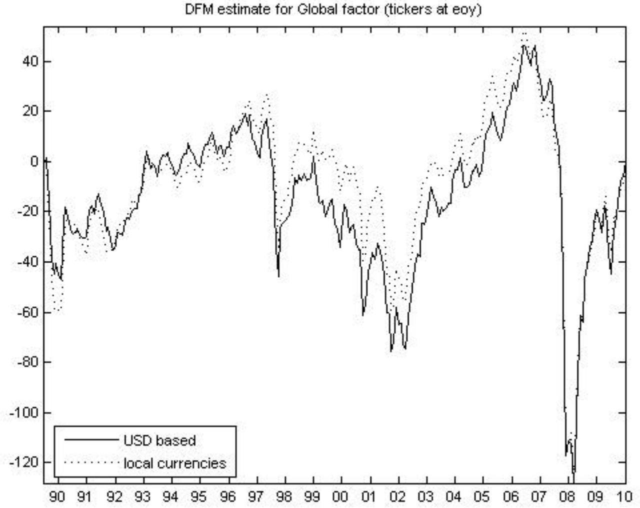
- τ is the hyperparameter controlling for the tightness of this prior; with $\tau \to \infty$ the prior is uninformative.

PRIORS

Regional Factors

BackToGlobalFactorChart

Global factor from data in local currencies



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Countries in Global Data

Table: **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.

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Global Domestic Credit Data

- Global Domestic Credit is constructed as the cross-sectional sum of National Domestic Credit data.
- National Domestic Credit is calculated as the difference between Domestic Claims to All Sectors and Net Claims to Central Government [Gourinchas and Obstfeld (2012)]:
  - Claims to All Sectors are calculated 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.
  - Net Claims to Central Government are calculated as the difference between Claims on and Liabilities to Central Government
- Raw data in national currency.
- *Source:* IFS, Other Depository Corporation Survey and Deposit Money Banks Survey (prior to 2001).

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Global Cross Border Credit Data

- Global Inflows are calculated as the cross-sectional sum of national Cross Border Credit data.
- 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 in a selection of countries. [Avdjiev, McCauley and McGuire (2012)]
- Raw data in Million USD.
- *Source:* BIS, Locational Banking Statistics Database, External Positions of Reporting Banks vis-à-vis Individual Countries (Table 6).

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Global Banks Leverage

- Leverage Ratios for the Global Systemic Important Banks in the Euro-Area and United-Kingdom are constructed as weighted averages of individual banks data.
- Individual banks leverage ratios are computed as the ratio between aggregate Balance sheet Total Assets (DWTA) and Shareholders' Equity (DWSE).
- Weights are proportional to Market Capitalization (WC08001).
- *Source:* Thomson Reuter Worldscope Datastream.

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Aggregate Banking Sector Leverage

- 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.
- Aggregate country-level measures of banking sector leverage are built as the ratio between Claims on Private Sector and Transferable plus Other Deposits included in Broad Money of depository corporations excluding central banks.[Forbes (2014)]
- Raw data in local currency.
- *Source:* IFS, Other Depository Corporation Survey and Deposit Money Banks Survey (prior to 2001).

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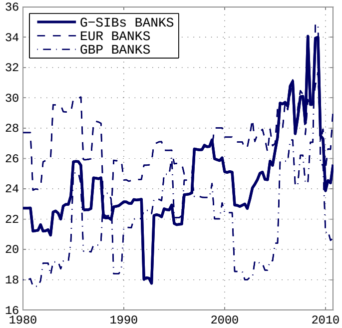
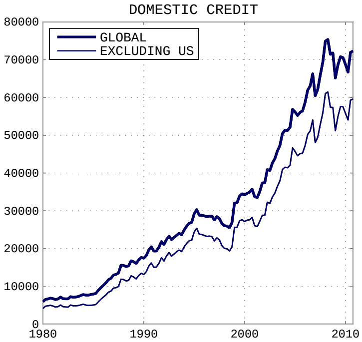
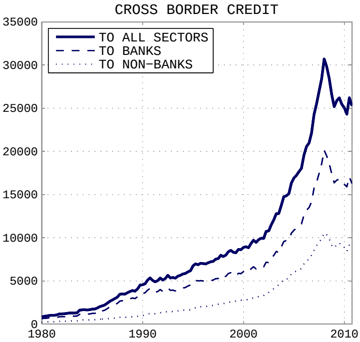
Leverage of Banks



flows

Credit Aggregates





flows

Proxy SVAR

- Achieve identification using a proxy variable that is correlated with the shock of interest but not correlated with any other shock in the system [Merten and Ravn (2013), Stock and Watson (2012), Gertler and Karadi (2013)];
- if such an instrument z_t exists, and there is only one shock of interest, then closed form solutions for the identified parameters exist and they are only function of sample moments.