US Monetary Policy and the Global Financial Cycle

Silvia Miranda-Agrippino and Hélène Rey
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

Dynamic Factor Model for Risky Assets

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

\[
\text{return } (i,t) = \text{global factor } (t) + \text{regional factors } (t) + \text{idiosyncratic } (i,t)
\]

- Each return series is the sum of three components:

\[
y_{i,t} = \mu_i + \lambda_{i,g}f_{t}^g + \lambda_{i,m}f_{t}^m + \xi_{i,t}.
\]  

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
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

<table>
<thead>
<tr>
<th>Year</th>
<th>North America</th>
<th>Latin America</th>
<th>Europe</th>
<th>Asia Pacific</th>
<th>Australia</th>
<th>Cmdy</th>
<th>Corporate</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990:2012</td>
<td>364</td>
<td>16</td>
<td>200</td>
<td>143</td>
<td>21</td>
<td>57</td>
<td>57</td>
<td>858</td>
</tr>
</tbody>
</table>

*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)]

\begin{equation}
    y_t = \mu + \Lambda f_t + \xi_t, \tag{2}
\end{equation}

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

• $\xi_t$ 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:

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

Table: **Number of Factors**

<table>
<thead>
<tr>
<th>$r$</th>
<th>% Cov Mat</th>
<th>% Spec Den</th>
<th>$IC_{p1}$</th>
<th>$IC_{p2}$</th>
<th>$IC_{p3}$</th>
<th>Bai Ng (2002)</th>
<th>Onatski</th>
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</thead>
<tbody>
<tr>
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<td>(a) 1975:2010</td>
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<tr>
<td>1</td>
<td>0.662</td>
<td>0.579</td>
<td>-0.207</td>
<td>-0.204</td>
<td>-0.217</td>
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<td>2</td>
<td>0.117</td>
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<td>-0.179</td>
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<tr>
<td>3</td>
<td>0.085</td>
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<td>-0.179</td>
<td>0.360</td>
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<tr>
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<td>0.028</td>
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<td>-0.110</td>
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<td>0.024</td>
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<td>-0.079</td>
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<td>(b) 1990:2012</td>
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<td>0.241</td>
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<td>-0.183</td>
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<tr>
<td>2</td>
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<td>-0.156</td>
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<tr>
<td>3</td>
<td>0.036</td>
<td>0.071</td>
<td>-0.133</td>
<td>-0.129</td>
<td>-0.148</td>
<td>0.790</td>
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<tr>
<td>4</td>
<td>0.033</td>
<td>0.056</td>
<td>-0.107</td>
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<td>-0.128</td>
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</tr>
<tr>
<td>5</td>
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<td>-0.082</td>
<td>-0.075</td>
<td>-0.108</td>
<td>0.531</td>
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</tr>
</tbody>
</table>

**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.

![Graph of Global Common Factor from 1975 to 2010](image)

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

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

G-SIBs (25)

Commercial Banks (122)

Capital Markets (18)

Other Financial (14)
Banks and the Global Factor

Full Sample (162)
(a)

G-SIBs (20)
(c)

average return
pre crisis

average return
post crisis

average β pre crisis

average β pre crisis

(b)

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

\[
\max_{x_t^B} \mathbb{E}_t \left( x_t^B' R_{t+1} \right)
\]

\[
s.t. \ VaR_t \leq w_t^B,
\]

where the VaR is defined as a multiple \(\alpha\) of the standard deviation of the bank portfolio

\[
VaR_t = \alpha w_t^B \left[ \mathbb{V}_t \left( x_t^B' R_{t+1} \right) \right]^{\frac{1}{2}}.
\]
The vector of asset demands for global banks is given by:

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

The VaR constraint plays a role similar to risk aversion; $\lambda_t$ is the lagrange multiplier of the constraint.
Risk Averse Mean-Variance Investors

- Mean variance investors problem:

$$\max_{x^I_t} \mathbb{E}_t \left( x^I_t' R_{t+1} + y^I_t' R^{NT}_{t+1} \right) - \frac{\sigma}{2} \mathbb{V}_t (x^I_t' R_{t+1} + y^I_t' R^{NT}_{t+1})$$

- resulting optimal portfolio choice in risky tradable securities:

$$x^I_t = \frac{1}{\sigma} \left[ \mathbb{V}_t (R_{t+1}) \right]^{-1} \left[ \mathbb{E}_t (R_{t+1}) - \sigma \text{cov}_t (R_{t+1}, R^{NT}_{t+1}) y^I_t \right]$$ (4)
Time varying effective risk aversion of the market

• The market clearing condition for risky assets is

\[ x^B_t \frac{w^B_t}{w^B_t + w^I_t} + x^I_t \frac{w^I_t}{w^B_t + w^I_t} = s_t, \]

where \( s_t \) is the world vector of net asset supplies for traded assets.

• It follows that:

\[ \mathbb{E}_t (R_{t+1}) = \Gamma_t \left[ \nabla_t(R_{t+1})s_t + \text{cov}_t(R_{t+1}, R^N_{t+1})y_t \right], \]

where \( \Gamma_t \equiv \frac{w^B_t + w^I_t}{w^B_t + w^I_t} \) 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:

\[
E_t (R_{t+1}) = \Gamma_t \left[ V_t (R_{t+1}) \right] s_t + \Gamma_t \text{cov}_t (R_{t+1}, R_{t+1}^{NT}) y_t
\]

- 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 \( \Gamma_t \) and on aggregate uncertainty \( V_t (R_{t+1}) \).

- 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($p$):

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

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 $\theta$. This distribution depends on a set of hyperparameters $\gamma$: $p_\gamma(\theta)$.

• 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 $\gamma$ 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 $\gamma$ 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 $\text{eye}(n)$ and all other $A_i$ matrices ($i = 2, \ldots, p$) towards zero.

- Problem: $\mathbb{E}(u_t u_t') = \text{diag}(Q)$!
The NIW prior (2)

- The NIW solution:

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

where \( \beta \) is a vector collecting all VAR parameters.

- \( \nu = n + 2 \) ensures the mean of \( \mathcal{W}^{-1} \) exists.

- \( \Psi = \text{diag}(\psi_i) \) is a function of the residual variance of \( AR(p) \), \( \forall y_i \in Y_t \).

- Other parameters are chosen to match:

\[ \mathbb{E}[(A_i)_{jk}] = \begin{cases} \delta_j & i = 1, j = k \\ 0 & \text{otherwise} \end{cases} \quad \text{Var}[(A_i)_{jk}] = \begin{cases} \frac{\lambda^2}{\tau_2} & j = k \\ \frac{\lambda^2}{\tau_2} \frac{\sigma_k^2}{\sigma_j^2} & \text{otherwise} \end{cases} \]

- \( \lambda = 0 \) 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:

\[ Y = XB + U, \]

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

- Dummy observations:

\[ Y_{NIW} = \left( \begin{array}{c}
\text{diag}(\delta_1 \sigma_1, \ldots, \delta_n \sigma_n)/\lambda \\
0_{n(p-1) \times n} \\
\text{diag}(\sigma_1, \ldots, \sigma_n) \\
\cdots \\
0_{1 \times n}
\end{array} \right) \quad X_{NIW} = \left( \begin{array}{c}
J_p \otimes \text{diag}(\sigma_1, \ldots, \sigma_n)/\lambda \\
\cdots \\
0_{n \times np} \\
0_{1 \times np}
\end{array} \right) \bigg| \begin{array}{c}
0_{np \times 1} \\
\cdots \\
0_{n \times n}
\end{array}. \]

- \( J_p \equiv \text{diag}(1, \ldots, p) \) and \( \epsilon \) 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:

  $$Y_{SoC} = \text{diag} \left( \frac{\bar{Y}}{\mu} \right) \quad X_{SoC} = \left( \text{diag} \left( \frac{\bar{Y}}{\mu} \right) \; \ldots \; \text{diag} \left( \frac{\bar{Y}}{\mu} \right) \; 0_{n \times 1} \right)$$

- $\bar{Y}$ denotes the sample average of the initial $p$ observations per each variable and $\mu$ is the hyperparameter controlling for the tightness of this prior; with $\mu \to \infty$ the prior is uninformative.
• 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:

\[
Y_{Coin} = \frac{\bar{Y}'}{\tau} \quad X_{Coin} = \frac{1}{\tau} \left( \begin{array}{cccc}
\bar{Y}' & \ldots & \bar{Y}' & 1
\end{array} \right)
\]

• \(\tau\) is the hyperparameter controlling for the tightness of this prior; with \(\tau \to \infty\) the prior is uninformative.
Regional Factors

ASIA PACIFIC

AUSTRALIA

EUROPE

LATIN AMERICA

NORTH AMERICA

CORPORATE

COMMODITY
Global factor from data in local currencies
## Countries in Global Data

### Table: List of Countries Included

<table>
<thead>
<tr>
<th>North America</th>
<th>Latin America</th>
<th>Central and Eastern Europe</th>
<th>Western Europe</th>
<th>Emerging Asia</th>
<th>Asia Pacific</th>
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**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.
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).
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).
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 Worldscape Datastream.
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).
Leverage of Banks

![Graph showing leverage of banks from 1980 to 2010 for G-SIBs, EUR, GBP banks, and the banking sector.](image-url)
Credit Aggregates

DOMESTIC CREDIT
- GLOBAL
- EXCLUDING US

CROSS BORDER CREDIT
- TO ALL SECTORS
- TO BANKS
- TO NON-BANKS

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 [Mertens 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.