World Asset Markets and the Global Financial Cycle

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Motivation: era of financial globalization

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- What are the effects of large flows of credit and investments crossing borders 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?

Several related papers (I have been working on this topic....)

- Jackson Hole Paper, Rey (2013): Dilemma not Trilemma: The Global Financial Cycle and monetary policy independence
- Mundell Fleming Lecture, Rey (2014): International Channels of Transmission of Monetary Policy and the Mundellian Trilemma
- Sargan Lecture, Economic Journal, Passari and Rey (2015): Financial Flows and the International Monetary System
- Some new work with Elena Gerko on the UK and some new work with Nuno Coimbra on theory.

Strong common movements in gross capital flows

Liability	Equity	Equity	Equity	Equity	Equity	Equity	Equity	FDI	FDI	FDI	FDI	FDI	FDI	FDI	Debt	Debt	Debt	Debt	Debt	Debt	Debt	Credit	Credit	Credit	Credit	Credit	Credit	Credi
Flows	*N. Am.*	*LatAm*	*CE. EU*	*W. EU*	*Em.As*	*Asia*	*Africa*	*N. Am*	*LatAm*	*CE. EU*	*W. EU*	*Em.As*	*Asia*	*Africa*	*N. Am*	*LatAm*	*CE. EU*	*W. EU*	*Em.As*	*Asia*	*Africa*	*N. Am*	*LatAm*	*CE. EU*	*W. EU*	*Em.As*	*Asia*	*frica*
Equity N. Am	1.00																											
Equity LatAm	0.39	1.00																										
Equity CE. EU	0.52	0.49	1.00																									
Equity W. EU	0.63	0.35	0.50	1.00																								
Equity Em. As	0.37	0.24	0.28	0.47	1.00																							
Equity Asia	0.24	0.31	0.28	0.40	0.31	1.00																						
Equity Africa	0.41	0.22	0.26	0.55	0.34	0.26	1.00																					
FDI N. Am	0.54	0.06	0.07	0.45	0.52	-0.07	0.22	1.00																				
FDI LatAm	0.41	0.10	0.08	0.29	0.32	-0.07	0.04	0.68	1.00																			
FDI CE. EU	0.46	0.11	0.08	0.18	0.23	-0.12	0.09	0.61	0.65	1.00																		
FDI W. EU	0.57	0.21	0.19	0.38	0.35	0.01	0.16	0.61	0.59	0.75	1.00																	
FDI Em. As	0.47	0.24	0.16	0.34	0.36	-0.04	0.04	0.65	0.77	0.69	0.64	1.00																
FDI Asia	0.36	0.16	0.03	0.29	0.30	-0.17	0.05	0.60	0.70	0.57	0.51	0.69	1.00															
FDI Africa	0.33	0.01	0.10	0.18	0.03	-0.16	-0.19	0.31	0.36	0.35	0.35	0.34	0.27	1.00														
Debt N. Am	0.42	0.17	0.32	0.51	0.29	0.21	0.31	0.40	0.39	0.55	0.51	0.48	0.37	0.08	1.00													
Debt LatAm	0.20	0.40	0.33	0.16	0.13	0.00	-0.05	0.16	0.35	0.13	0.05	0.31	0.26	0.06	0.10	1.00												
Debt CE. EU	0.37	0.42	0.50	0.43	0.13	0.17	0.19	0.14	0.35	0.14	0.12	0.47	0.21	0.04	0.37	0.52	1.00											
Debt W. EU	0.49	0.05	0.33	0.50	0.23	0.27	0.47	0.29	0.10	0.44	0.27	0.25	0.02	0.10	0.58	-0.13	0.28	1.00										
Debt Em. As	0.40	0.58	0.65	0.35	0.20	0.23	0.20	0.13	0.24	0.25	0.37	0.35	0.15	0.02	0.32	0.38	0.53	0.14	1.00									
Debt Asia	0.16	0.18	0.24	0.22	0.16	-0.04	0.16	0.35	0.31	0.30	0.30	0.45	0.26	0.14	0.45	0.27	0.42	0.19	0.39	1.00								
Debt Africa	0.26	0.27	0.39	0.18	0.07	0.14	0.09	0.12	0.21	0.10	0.01	0.41	0.21	0.07	0.21	0.46	0.61	0.15	0.44	0.32	1.00							
Credit N. Am.	0.29	-0.02	0.21	0.38	0.15	-0.01	0.32	0.20	0.02	0.19	0.20	0.12	0.09	0.04	0.37	0.14	0.23	0.25	0.23	0.25	0.03	1.00						
Credit LatAm	0.41	0.34	0.21	0.26	0.12	0.04	0.22	0.38	0.35	0.42	0.27	0.48	0.35	0.24	0.35	0.25	0.41	0.30	0.29	0.46	0.28	0.22	1.00					
Credit CE. EU	0.42	0.25	0.27	0.28	0.32	0.15	0.21	0.54	0.38	0.72	0.55	0.47	0.36	0.28	0.54	0.14	0.13	0.56	0.25	0.48	0.12	0.17	0.55	1.00				
Credit W. EU	0.19	-0.03	0.24	0.31	0.19	-0.16	0.26	0.27	0.08	0.20	0.30	0.19	0.13	0.15	0.45	0.20	0.25	0.33	0.26	0.45	0.16	0.63	0.30	0.34	1.00			
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Figure: Gross inflows, all asset classes (FDI, debt, equity, bank credit), by geographical areas (North America, Western Europe, Latin America, Central and Eastern Europe, Asia, Emerging Asia, Africa). Green (Red) denote positive (negative) correlations. *Source:* Rey (Jackson Hole (2013))

Massive credit growth around the world

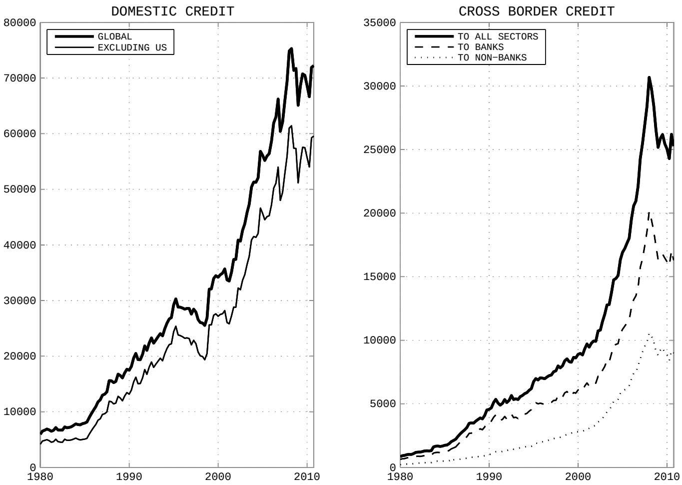

Figure: Domestic and cross border credit (world). *Source:* raw data from IFS and BIS, authors calculations.

ListOfCountries DcreditDataBuild CBcreditDataBuild

Increase in Financial Sector Leverage (EU)

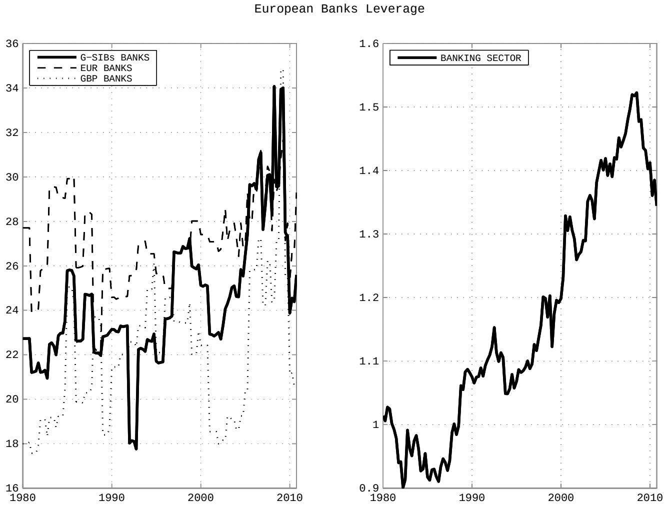

Figure: Banking Sector Leverage. *Source:* raw data from IFS, Bloomberg and Datastream, authors calculations.

GBleverageDataBuild BSleverageDataBuild

Leverage of G-SIBs

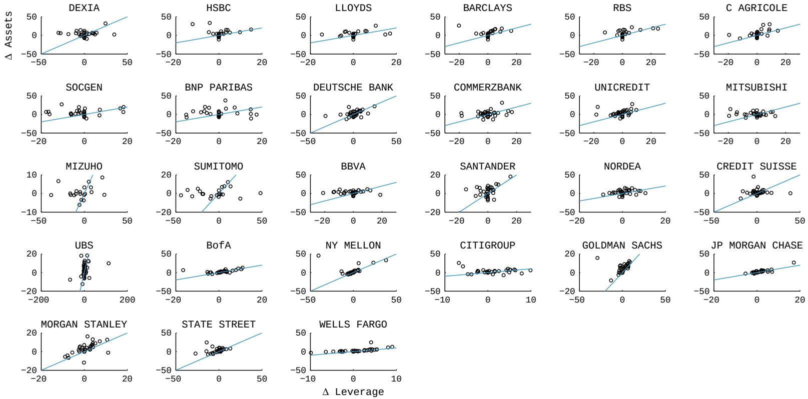

Figure: Quarterly growth of total assets over quarterly growth of leverage ratio, all available history. *Source:* Datastream, authors calculations

Global Financial Cycle

- Role of financial intermediaries and leverage (global banks) in transmitting financial conditions around the world (illustrative framework)

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- Role of financial intermediaries and leverage (global banks) in transmitting financial conditions around the world (illustrative framework)
- Document existence of Global Financial Cycle in risky asset prices in main financial markets around the world (DFM)
- Role of US Monetary Policy within the Global Financial Cycle: credit, risk premium, capital flows, real activity (large BVAR)
- International Channels of Transmission of Monetary Policy (Mundell Fleming Lecture)

Related Literature (subset!)

- Dynamic Factor models: Doz, Giannone and Reichlin (2006), Watson and Reis (2007), Bai and Ng (2004), Stock and Watson (2002), Forni, Hallin, Lippi and Reichlin (2005)
- Monetary policy VARs: Bekaert et al. (2012), Gertler and Karadi (2015), Banbura et al. (2013), Lenza et al. (2013), Dedola et al. (2015)
- Role of global banks and capital flows: Borio and Disyatat (2001), Bruno and Shin (2014), Cetorelli and Goldberg (2009, 2010), Fratzscher (2012), Forbes and Warnock (2014)
- Capital market imperfection, Financial intermediation: Bernanke and Gertler (1989), Kiyotaki and Moore (1997), Danielsson et al. (2009); Adrian and Shin (2010), Fostel and Geanakoplos (2009), Brunnermeier and Sannikov (2014), He and Krishnamurthy (2013), Adrian and Boyarchenko (2014)
- Monetary policy: Gertler and Kiyotaki (2014), Gertler and Karadi (2011), Farhi and Werning (2014, 2015), Curdia and Woodford (2009), Aoki et al. (2015)

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
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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 (1)

- 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 (2)

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

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

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

Risk Averse Mean-Variance Investors (1)

- 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:

$$\mathbf{x}_t^I = \frac{1}{\sigma} \left[\mathbb{V}_t (\mathbf{R}_{t+1}) \right]^{-1} \left[\mathbb{E}_t (\mathbf{R}_{t+1}) - \sigma cov_t (\mathbf{R}_{t+1}, \mathbf{R}_{t+1}^{NT}) \mathbf{y}_t^I \right] \quad (2)$$

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:

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

  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 aggregate degree of effective risk aversion Γ_t and on aggregate uncertainty $\mathbb{V}_t(\mathbf{R}_{t+1})$.
- Γ_t is a wealth-weighted average of the "risk aversion" parameters of the global banks and the asset managers.

Returns of Global Banks

- The expected excess return of a global bank portfolio in our economy:

$$\begin{aligned}\mathbb{E}_t(\mathbf{x}_t^{B\prime}\mathbf{R}_{t+1}) &= \left[cov_t(\mathbf{x}_t^{B\prime}\mathbf{R}_{t+1}, \mathbf{s}_t^{\prime}\mathbf{R}_{t+1}) + cov_t(\mathbf{x}_t^{B\prime}\mathbf{R}_{t+1}, \mathbf{y}_t^{\prime}\mathbf{R}_{t+1}^{NT})\right]\Gamma_t \\ &= \beta_t^{BW}\Gamma_t + \beta_t^{BN}\Gamma_t,\end{aligned}$$

  where β_t^{BW} is the beta of the assets of the global bank with the world market (systemic risk loading).

- Other things equal, the higher the degree of correlation with the world portfolio, the higher the expected return; this is equivalent to say that high β_t^{BW} global banks are those who loaded most on world risk.

Systemic Risk Loading of GB

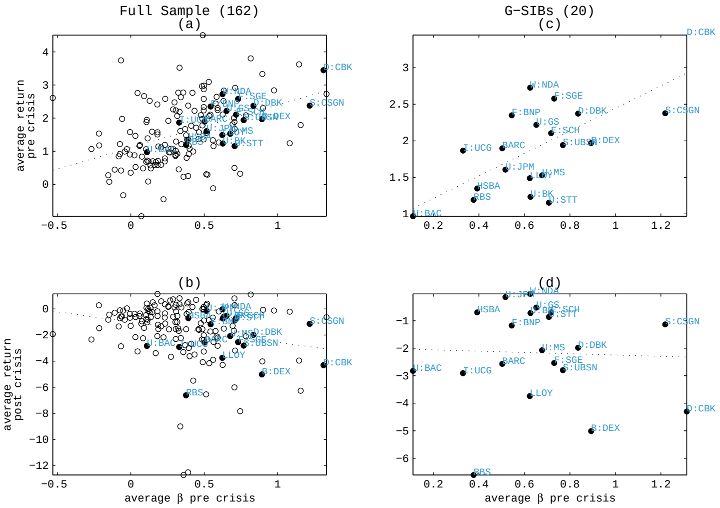


Figure: Pre and post crisis bank returns as a function of pre crisis betas.
Source: Datastream, authors calculations.

Dynamic Factor Model for Risky Assets

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

  return (i,t) = common component (t) + idiosyncratic (i,t)

- Using a set of restrictions on the coefficient matrices of the DFM we further decompose the common component in two:

  common (t) = global factor (t) + regional factors (t)

- Each return series is then the sum of three components:
  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
- Formally:

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

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: Specification and Estimation (1)

- The DFM is cast in state space form and estimated on the stationary return series using Maximum Likelihood = Kalman Filter + EM Algorithm [Doz, Giannone, Reichlin (2006), Watson, Reis (2007)]

- Factors for the price series are then obtained via cumulation [Bai, Ng (2004)]

- The number of factors [1 global & 1 per each block] and lag length of factors VAR [1] are selected using standard criteria and tests)

DFM for Risky Assets: Specification and Estimation (2)

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.

DFM for Risky Assets: Formalization

- 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)]

$$y_t = \mu + \Lambda f_t + \xi_t, \tag{4}$$

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: Dynamics

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

$$f_t = \Phi_1 f_{t-1} + \ldots + \Phi_p f_{t-p} + \varepsilon_t \tag{5}$$

  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 i.i.d. process with covariance matrix Q

- The idiosyncratic component is a collection of independent univariate autoregressive processes:

$$\xi_{i,t} = \rho_i \xi_{i,t-1} + e_{i,t} \tag{6}$$

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

DFM for Risky Assets: Block Structure (1)

- To distinguish between global and regional comovements we impose a block structure to the common component which is achieved via restrictions on the coefficients of the DFM [Banbura et al. (2010)]

- Active restrictions:

$$
\begin{aligned}
y_t &= \Lambda f_t + \xi_t & & \\
f_t &= \Phi(\mathrm{L}) f_{t-1} + \varepsilon_t & \varepsilon_t &\sim \mathcal{N}(0, Q) \\
\xi_{i,t} &= \rho_i \xi_{i,t-1} + e_{i,t} & e_{i,t} &\sim \mathcal{N}(0, \sigma_i^2)
\end{aligned}
$$

DFM for Risky Assets: Block Structure (2)

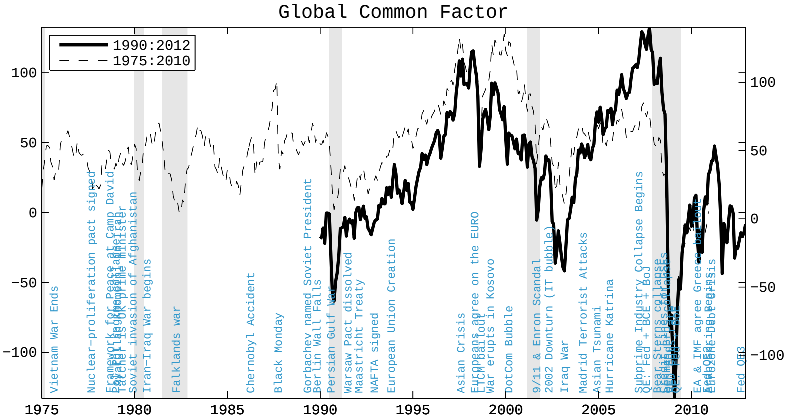
- Let the variables in y_t being univocally assigned to one of the nB postulated blocks.
- Order them accordingly such that $y_t = [y_t^1, y_t^2, \ldots, y_t^{nB}]'$; then:

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

DFM for Risky Assets: Estimation

- The model is estimated using maximum likelihood which is proven to be both consistent under misspecification of the factor structure and feasible for large N. [Doz, Giannone and Reichlin (2006)]
- In practical terms this is done by casting the DFM in state-space form and maximizing the likelihood via the EM algorithm that requires only one run of the Kalman filter/smoother at each iteration. [Engle and Watson (1981)]
- Principal component estimates of the factors are used to initialize the algorithm as they are proven to provide a good approximation of the factors when the cross-section is large.

Global Factor for World Asset Prices.



▸ RegionalFactors ▸ LocalCurrency

Global Factor and Risk in World Financial Markets

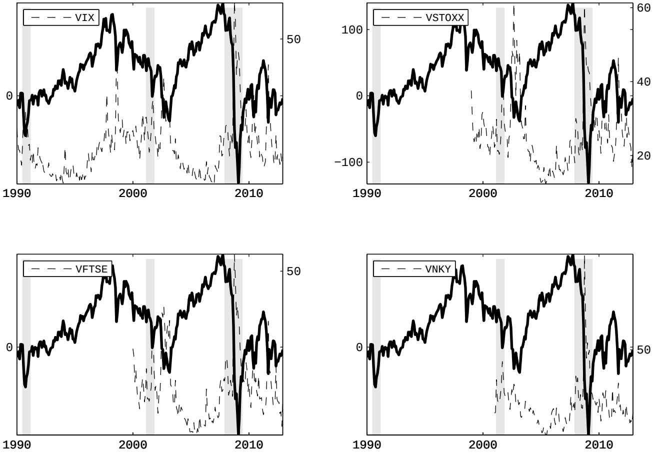


Figure: Global Factor (bold line) and major volatility indices (dotted lines); clockwise from top left panel: US; EU; JP and UK. *Source:* Datastream, authors calculations.

Global Factor and Credit Spreads

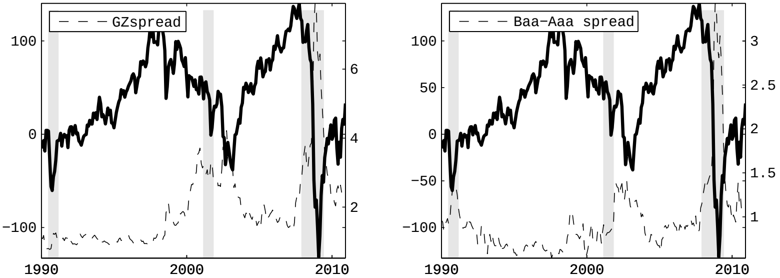


Figure: Global Factor (bold line) with the GZ spread (left) and the Baa-Aaa Corporate bond spread (right). *Source:* Gilchrist and Zakrajsek (2011), Datastream, authors calculations.

Global Factor Interpretation

- Recall from our theoretical framework:

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

- In a world financial market dominated by Global Banks, asset prices are a function of a Global Factor which is a function of global market variance and the aggregate degree of risk aversion in the market, itself a function of the risk taking attitude of the heterogeneous investors.

Model-Implied Global Factor Decomposition

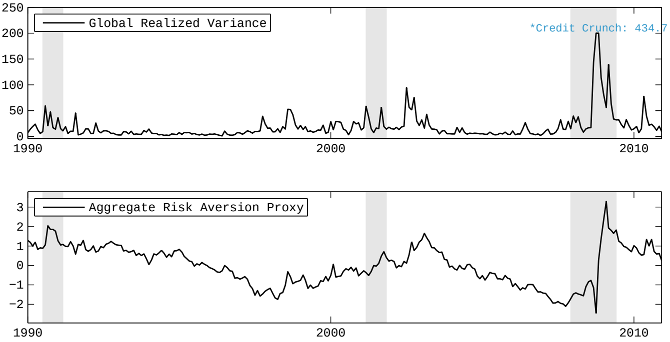


Figure: Decomposition of the global factor in a volatility component and a risk aversion component; the measure of realized monthly global variance is computed using daily returns of the MSCI world index. [Bollerslev et al. (2009)] *Source:* Datastream, authors calculations.

Monetary Policy, Markets and the Credit Cycle (1)

- How do large international flows of money affect the international transmission of monetary policy?
- We are interested in determining the role that monetary policy in the center country (US) plays in setting credit conditions worldwide and how this relates to global banks' risk taking behavior.
- Previous studies have analyzed the links between US monetary policy and risk [Bekaert et al. (2012)] and between monetary policy and capital flows with attention to the role played by global banks leverage [Bruno and Shin (2014)] in the context of small scale VARs.

Monetary Policy, Markets and the Credit Cycle (2)

- Small-scale VARs, while preferred for the limited number of parameters to be estimated, are naturally prone to criticism regarding omitted variable bias
- If a variable which is known to contain important structural information that is not already carried by the variables in the VAR is omitted, then the structural shocks cannot be in general be deduced from the VAR innovations [Stock and Watson (2005) among others]
- Further, variables omission may result in "puzzles" (i.e. price puzzles which are typically dealt with adding a commodity price index)

Monetary Policy, Markets and the Credit Cycle (3)

- We estimate a Bayesian VAR (in levels) with 4 lags where we augment the typical set of macroeconomic variables, including output, inflation, investment and labor data, with our variables of interest: global credit, cross border flows, financial leverage, asset prices, risk premium, term spread.

- The monetary policy shock is identified using the effective federal funds rate as the instrument for monetary policy and block-ordering the variables into slow-moving and fast-moving ones. Fast-moving variables are allowed to respond to the MP shock within the quarter.

Monetary Policy, Markets and the Credit Cycle (4)

ID	Name	Logs	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	

▸ DcreditDataBuild ▸ CBcreditDataBuild ▸ GBleverageDataBuild ▸ BSleverageDataBuild

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):

$$Y_t = C + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + u_t \qquad (7)$$

  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.

DetailsOnPriors

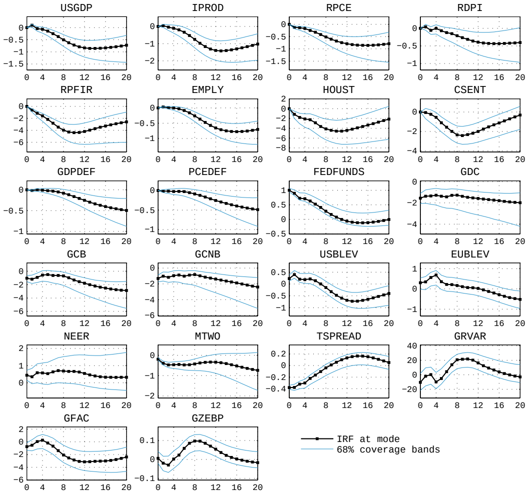
BVAR results (1)

- In our baseline specification, the BVAR is estimated in levels using 4 lags (3 and 5 give virtually same results) on 22 variables
- The set of standard variables used includes: output, consumption, investments, employment, income, construction, expectations, prices, money
- The monetary policy instrument is the effective federal fund rate
- To these we add our variables of interest: domestic and cross border credit, global banks leverage, market variance, the global asset prices factor

BVAR results (2)

- Results are expressed in terms of impulse response functions and depict responses to a monetary policy shock which induces a 100 basis points increase in the effective federal fund rates.
- IRFs calculated at the mode of the posterior distribution are plotted together with 68% coverage bands (corresponding to 1 standard error, obtained as the 16th and 84th quantile).
- Responses are expressed in percentage points; interest rates and the excess bond premium are also in the same unit.

BVAR results (3): Full Baseline



BVAR results (4): Detail on Credit

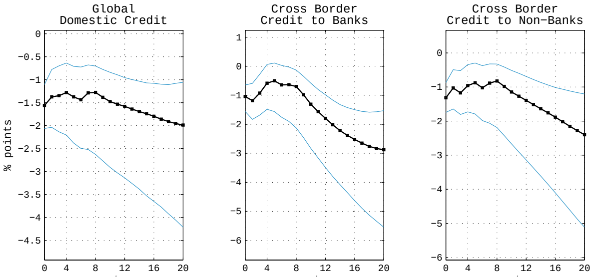


Figure: Response of Global Credit (% points) to a monetary policy shock inducing a 100bp increase in the Effective Fed Funds Rate.

BVAR results (5): Detail on Banking Sector Leverage

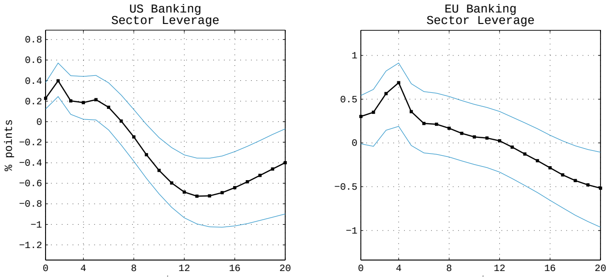


Figure: Response of Banking Sector Leverage (% points) to a monetary policy shock inducing a 100bp increase in the Effective Fed Funds Rate.

BVAR results (6): Detail on Financial

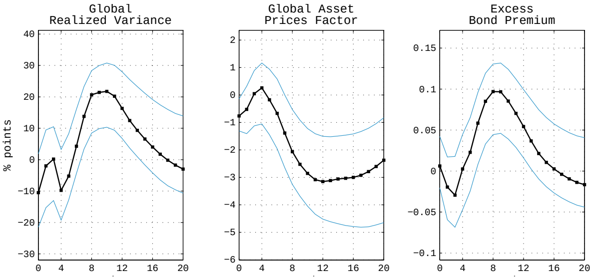


Figure: Response of Global Financial Variables (% points) to a monetary policy shock inducing a 100bp increase in the Effective Fed Funds Rate.

BVAR results (7)

- Two additional exercises:
- split Global Domestic Credit into US Domestic Credit and Rest of the World
- substitute banking sector leverage with the leverage of global banks: US broker and dealers and European global systemically important banks (GSIBs)
- In both cases the BVAR includes 4 lags. IRFs for the other variables included in the system are unchanged

BVAR results (8): Detail on Credit (2)

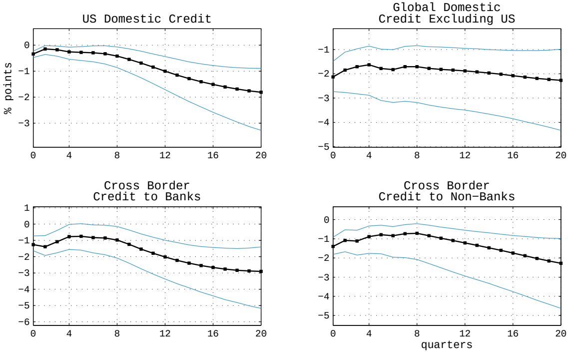


Figure: Response of Global Credit (% points) to a monetary policy shock inducing a 100bp increase in the Effective Fed Funds Rate.

BVAR results (9): Detail on Leverage (2)

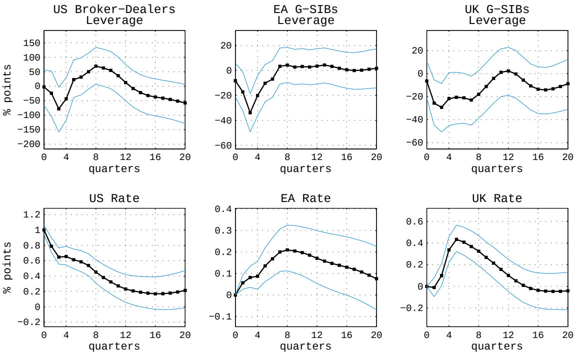


Figure: Response of Global Banks Leverage and Funding Costs (% points) to a monetary policy shock inducing a 100bp increase in the Effective Fed Funds Rate.

Proxy SVAR (1)

- 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)];

- Let z_t denote the proxy variable and partition the vector of reduced form VAR innovations

$$u_t = \begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix}$$

  where $u_{1,t}$ are the innovations of the policy variable;

- the procedure can be thought of in terms of instrumental variable estimation: the proxy variable is used as an instrument for $u_{1,t}$ in a regression of $u_{2,t}$ over $u_{1,t}$.

Proxy SVAR (2)

- The conditions under which identification is achieved are:

$$\mathbb{E}(z_t e'_{1,t}) = \kappa \qquad\qquad \mathbb{E}(z_t e'_{2,t}) = 0 \tag{8}$$

  where e_{1t} is the structural shock of interest;

- 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.

Proxy Variable for US Monetary Policy (1)

- Construct a narrative-based instrument that isolates changes in FFR which deviate from the set targets and are orthogonal to current and expected economic conditions [Romer and Romer (2004)]

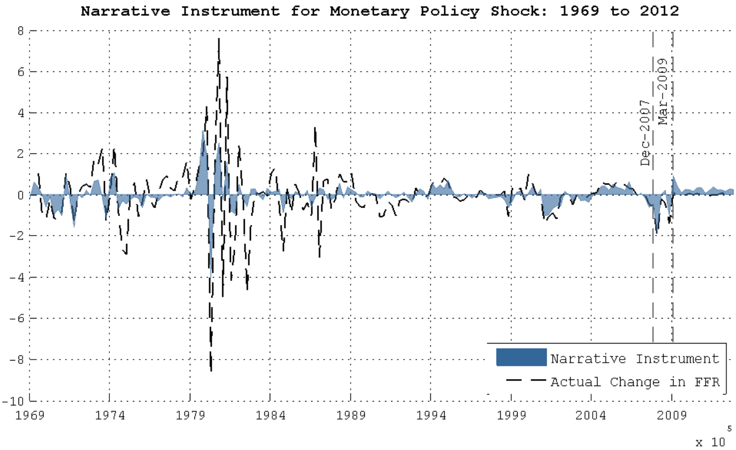
$$\begin{aligned}\Delta FFR_m =& \alpha + \beta FFR_m + \rho u^{(m)}_{t+0|t} \\ &+ \sum_{j=-1}^{2} \gamma_j y^{(m)}_{t+j|t} + \sum_{j=-1}^{2} \lambda_j \left[y^{(m)}_{t+j|t} - y^{(m-1)}_{t+j|t} \right] \\ &+ \sum_{j=-1}^{2} \phi_j \Delta\pi^{(m)}_{t+j|t} + \sum_{j=-1}^{2} \theta_j \left[\Delta\pi^{(m)}_{t+j|t} - \Delta\pi^{(m-1)}_{t+j|t} \right] + \varepsilon_m; \qquad (9)\end{aligned}$$

where m denotes FOMC meeting; ΔFFR_m is the target FFR change; FFR_m is the level of the rate before the FOMC; u, y and π denote the unemployment rate, real output growth and inflation; $t + j|t$ denotes forecasts for quarter $t + j$.

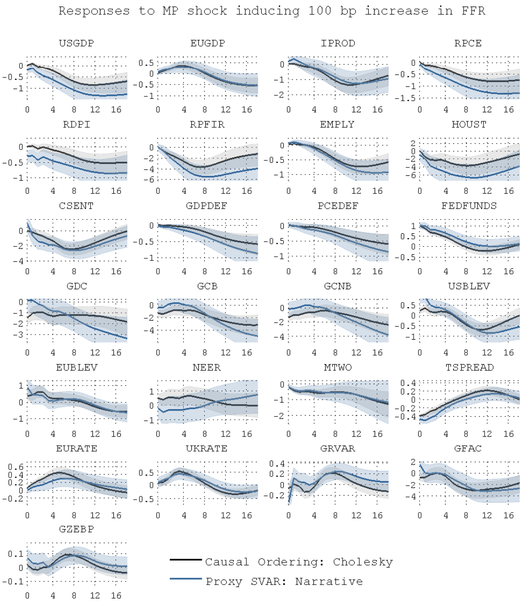
Proxy Variable for US Monetary Policy (1)

- Our extension covers the period 1997-2012 and the same methodology is adopted throughout the sample;
- exceptions are:
    - from 2008 Greenbook forecasts are substituted with the Philadelphia Fed SPF;
    - from September 2008 the FFR target is specified as a range, we take the mid point as the new target.

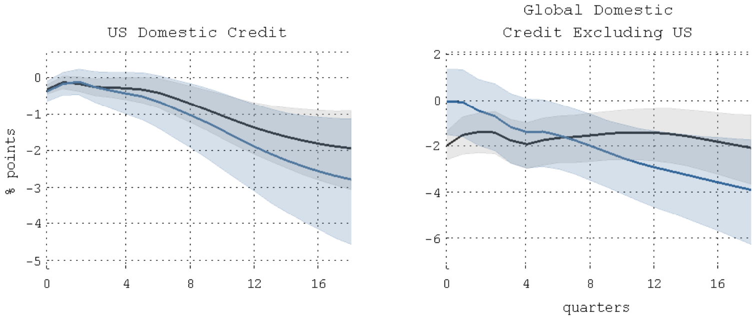
Proxy Variable for US Monetary Policy (2)



IRF (1)

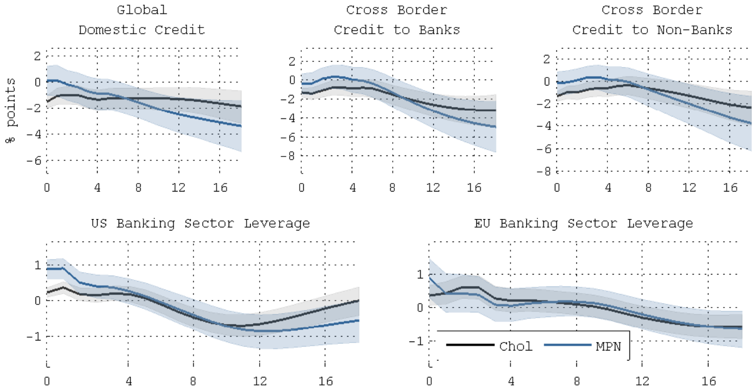

Responses to MP shock inducing 100 bp increase in FFR
USGDP
EUGDP
IPROD
RPCE
RDPI
RPFIR
EMPLY
HOUST
CSENT
GDPDEF
PCEDEF
FEDFUNDS
GDC
GCB
GCNB
USBLEV
EUBLEV
NEER
MTWO
TSPREAD
EURATE
UKRATE
GRVAR
GFAC
GZEBP
Causal Ordering: Cholesky
Proxy SVAR: Narrative

IRF (2)



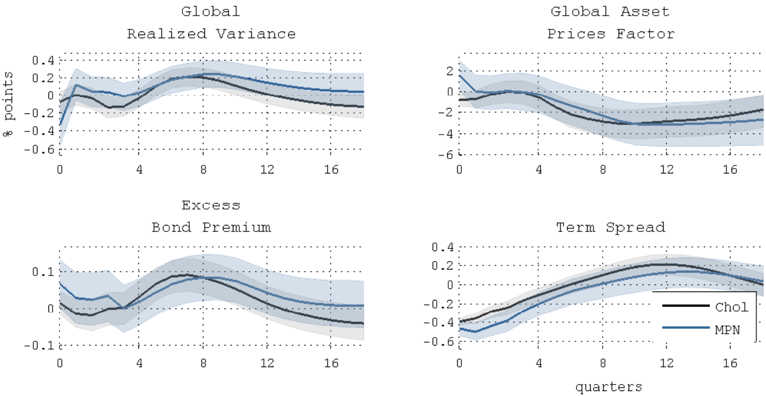
US Domestic Credit
Global Domestic
Credit Excluding US
% points
0
-1
-2
-3
-4
-5
2
0
-2
-4
-6
0
4
8
12
16
0
4
8
12
16
quarters

IRF (3)



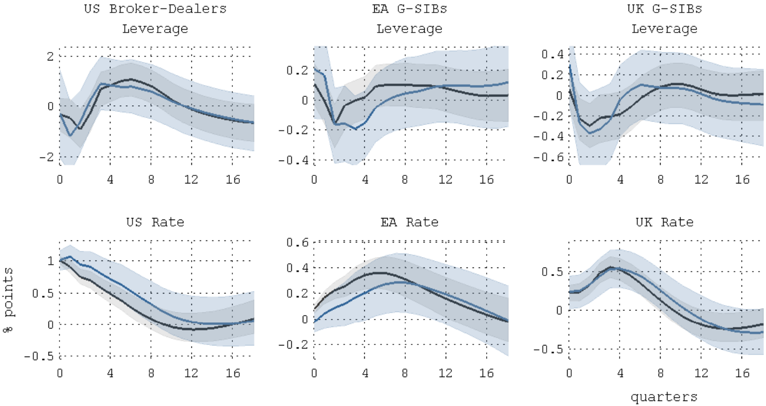
Global
Domestic Credit
Cross Border
Credit to Banks
Cross Border
Credit to Non-Banks
% points
US Banking Sector Leverage
EU Banking Sector Leverage
Chol
MPN

IRF (4)



Global
Realized Variance
% points
0.4
0.2
0
-0.2
-0.4
-0.6
0
4
8
12
16
Global Asset
Prices Factor
2
0
-2
-4
-6
0
4
8
12
16
Excess
Bond Premium
0.1
0
-0.1
0
4
8
12
16
Term Spread
0.4
0.2
0
-0.2
-0.4
-0.6
Chol
MPN
0
4
8
12
16
quarters

IRF (5)

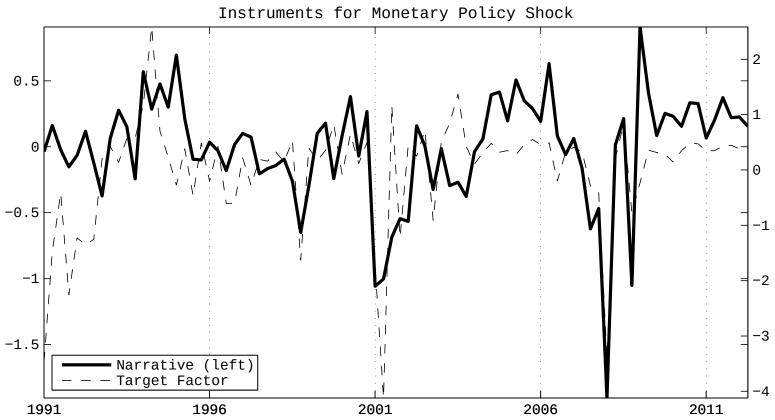


US Broker-Dealers Leverage
EA G-SIBs Leverage
UK G-SIBs Leverage
US Rate
EA Rate
UK Rate
% points
quarters

Conclusions

- One global factor explains an important part of the variance of a large cross section of returns of risky assets around the world.
- Large Bayesian VAR allows us 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.
- US monetary policy is a driver of the global factor in asset prices, of the term spread and of 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.
- Implications for theoretical modelling of monetary policy transmission.
- Thank you!

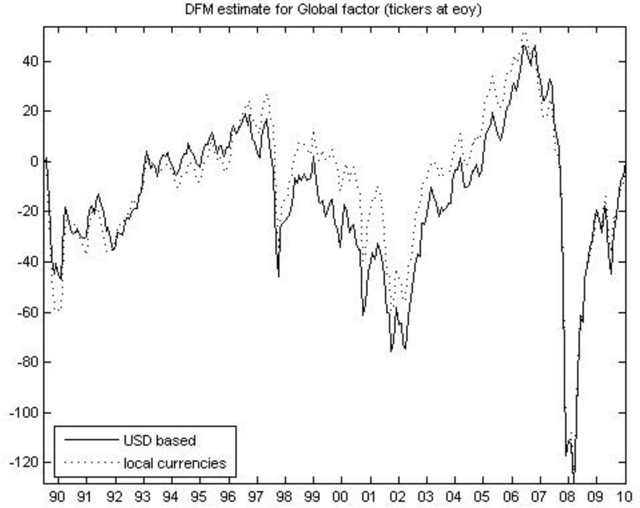
Proxy Variables for US Monetary Policy



Regional Factors

▸ BackToGlobalFactorChart

Global factor from data in local currencies



BackToGlobalFactorChart

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.

BackToIntro

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.

▸ BackToIntro ▸ BackToBVAR

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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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: $\mathbb{E}(u_t u_t') = diag(Q)$!

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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.

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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:

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

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

▸ BackToBVAR

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.

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Additional Priors (2)

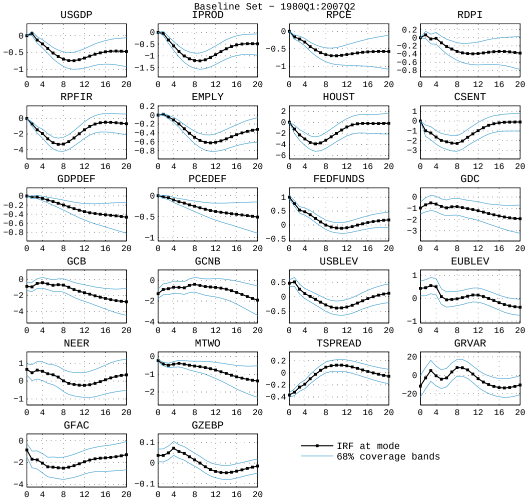
- Modification to sum-of-coefficients prior to allow for cointegration (Coin) [Sims (1993)]:
  - No-change forecast *for all variables* at the beginning of the sample is a good forecast;
  - It is implemented adding 1 artificial observation:

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

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

BackToBVAR

BVAR robustness (1): 1980:2007



BVAR robustness (1): EU cycle