World Asset Markets and Global Liquidity

[provisional title]

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Abstract

We show that one global factor explains most of the variance of a large cross section of the price of risky assets around the world. This global factor is inversely related to the VIX and can be interpreted as measuring the time varying degree of risk aversion of global banks, who fund themselves largely on dollar markets. In turn we relate this time varying risk aversion to the leverage of global banks and investigate its links with monetary policy.

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1 Introduction

2 The Model

We are not wedded to a model, but for illustrative purposes, we use here the set up of Danielsson, Shin and Zigrand (2011) and simplified by Adrian and Shin (2011a).

We consider a world in which there are global banks, i.e. leveraged entities which operate on all main asset markets and fund themselves in great part in dollars. There are also passive investors, which will be more precisely defined below. We assume global banks are risk neutral, and that bank equity is sticky: for reasons left unmodelled, it is very costly for a bank to adjust its equity level. Instead, during booms, banks increase the size of their balance sheets and become more leveraged. Adrian and Shin (2011b) provides ample evidence on the procyclicality of leveraged financial intermediaries balance sheets.

Global banks maximize the expected return of their portfolio of world risky assets subject to a Value at Risk constraint. The VaR is the most a bank is predicted to lose with a certain probability. The VaR will be here taken to be proportional to the volatility of the bank risky portfolio. We denote by $\mathbf{x}_t^B$the vector of wealth invested in risky assets for a global bank and by $\mathbf{R}_t$ the vector of excess returns of all risky assets in the world. We call w_t^B the equity of the bank.

A global bank maximizes

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

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

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

Writing the Lagrangian of the maximization problem and taking the first order condition gives the following solution for the vector of asset demands (where λ_t is the Lagrange multiplier):

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

This is the usual allocation of a mean variance investor. In this set up the VaR constraint plays the same role as risk aversion.

Because investors are risk neutral, the constraint is binding and

$$k \left(Var_t \left(\mathbf{x}_t^{B\prime}\mathbf{R}_{t+1}\right)\right)^{1/2} = 1$$

which implies

$$\lambda_t = \sqrt{E_t \left(\mathbf{R}_{t+1}\right)' \left[Var_t(\mathbf{R}_{t+1})\right]^{-1} E_t \left(\mathbf{R}_{t+1}\right)}$$

As in Adrian and Shin (2011), we now introduce standard mean variance investors (pension funds, households, etc...). We denote by σ their degree of risk aversion. They have access to the same set of assets as the global banks. The vector of asset demands will be given by the usual formula

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

The market clearing condition is

$$\mathbf{x}_t^B \frac{w_t^B}{w_t^B + w_t^P} + \mathbf{x}_t^P \frac{w_t^P}{w_t^B + w_t^P} = \mathbf{s}_t$$

where $\mathbf{s}_t$ is a vector of net asset supplies.

Using 1 and 2 we can then derive

$$E_t \left(\mathbf{R}_{t+1}\right) = \left[Var_t(\mathbf{R}_{t+1})\right] \ \mathbf{s}_t \frac{w_t^B + w_t^P}{\frac{w_t^B}{k\lambda_t} + \frac{w_t^P}{\sigma}}$$

which can be rewritten (by denoting $\frac{w_t^B + w_t^P}{\frac{w_t^B}{k\lambda_t} + \frac{w_t^P}{\sigma}} = \Gamma_t$) as

$$E_t \left(\mathbf{R}_{t+1}\right) = \left[Var_t(\mathbf{R}_{t+1})\right] \ \Gamma_t \ \mathbf{s}_t \tag{3}$$

Γ_t is just the wealth weighted combination of effective risk aversion and can be interpreted as the aggregate degree risk aversion of the market.

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

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

where β_t^{BW} is the beta of the global bank with the world market, the more correlated a global bank portfolio with the world portfolio, the higher the expected asset return. This is equivalent to saying that the high β_t^{BW} global banks are the ones which loaded most on world risk. The excess return is scaled up by the global degree of risk aversion. Γ_t in the economy.

It is possible to link the aggregate degree of risk aversion to the degree of leverage of the different financial institutions. Using 3 and 1, we can get

$$\mathbf{x}_t^B = \frac{1}{k\lambda_t}\Gamma_t\mathbf{s}_t$$

Post multiplying by the vector **1,** we get $\mathbf{x}_t^{B\prime}.\mathbf{1}{=}\frac{1}{k\lambda_t}\Gamma_t\mathbf{s}_t^{\prime}.\mathbf{1}$

Using the balance sheet identity of banks, where the value of assets (investment in risky securities) must equal the value of liabilities (debt D_t^B and bank equity w_t^B) we have

$$w_t^B\mathbf{x}_t^{B\prime}.\mathbf{1} = w_t^B + D_t^B$$

The leverage ratio of a global bank is defined as total assets over bank equity:

$$L_t^B = \frac{w_t^B\mathbf{x}_t^{B\prime}.\mathbf{1}}{w_t^B} = \frac{w_t^B + D_t^B}{w_t^B} = w_t^B\mathbf{x}_t^{B\prime}.\mathbf{1}$$

The leverage ratio of all financial institutions is

$$L_t^{B+P} = \frac{w_t^B + w_t^P + D_t^B + D_t^P}{w_t^P + w_t^B} = \mathbf{s}_t'.\mathbf{1}$$

We can now rewrite Γ_t as

$$\Gamma_t = \sigma \left[1 + \frac{w_t^B}{w_t^P} \left(1 - \frac{L_t^B}{L_t^{B+P}} \right) \right]$$

As pointed out by Adrian and Shin (2011), the aggregate effective risk aversion of the market can be expressed as a function of the leverage of banks relative to the market and the relative wealth of global banks compared to mean variance investors.

Using the definition of the expected excess asset returns on risky securities i $E_t R_{t+1}^i = \frac{E_t(P_{t+1}^i)+\delta_t^i}{\acute{P}_t^i} - r_t^{US}$ where δ_t is the dividend payment and r_t^{US} is the dollar refinancing rate, we can now rewrite the risky asset price P_t^i as

$$\begin{aligned} P_t^i E_t R_{t+1}^i + \acute{P}_t^i r_t^{US} - E_t(P_{t+1}^i) = \delta_t^i \\ P_t^i &= \frac{\delta_t^i}{E_t R_{t+1}^i + r_t^{US} - \alpha} \\ P_t^i &= \frac{\delta_t^i}{\Gamma_t \left[\left[Var_t(\mathbf{R}_{t+1}) \right] \ \mathbf{s}_t \right]_i + r_t^{US} - \alpha} \end{aligned}$$

where we used

$$P_t^i (1 - r_t^{US}) = \Gamma_t \left[\left[Var_t(\mathbf{R}_{t+1}) \right] \ \mathbf{s}_t \right]_i$$

and we postulated an autoregressive process for P_t^i of the form

$$P_{t+1}^i = \alpha P_t^i + \epsilon_{t+1}$$

The price of a risky asset in our model is therefore given by

$$P_t^i = \frac{\frac{\delta_t^i}{r_t^{US} - \alpha}}{\frac{\Gamma_t}{r_t^{US} - \alpha} \left[\left[Var_t(\mathbf{R}_{t+1}) \right] \ \mathbf{s}_t \right]_i + 1} \tag{4}$$

It is decreasing in the global factor $\frac{\Gamma_t}{r_t^{US}-\alpha}$, scaled up by a factor $[[Var_t(\mathbf{R}_{t+1})]\ \mathbf{s}_t]_i$ which involves the aggregate level of volatility of the market. In our set up, asset prices are therefore increasing when aggregate market volatility declines, when the refinancing cost r_t^{US} goes down, when dividends go up and when the degree of aggregate effective risk aversion Γ_t goes down. From the calculations above, Γ_t goes down when the leverage of global banks goes up and when the wealth share of global banks in total wealth is high. In the empirical part of the paper, we i) document the international funding flows and investment of global banks [in progress]; ii) we test 4 in a broad cross section of risky assets; iii) we study the time variation of the return and leverage of global banks [preliminary].

3 Empirical asset Pricing Implications of Global Banks

In this section we exploit the properties of a panel of risky asset prices in order to analyze the main sources of variation that contribute to their evolution. According to equation 4 (MAKE DYN REF HERE) in our model, the price of a risky asset is determined by both global and asset specific factors, with the former being formally linked to the aggregate degree of risk aversion of the market. Therefore, to empirically match the different level of aggregation of these common components, we will distinguish between global, regional, and asset specific signals to isolate those components that are common to all asset categories irrespective of the geographical location of the market in which the assets are traded or the specific asset class they belong to.

More formally, let x_t be an $N \times 1$ vector collecting monthly price series x_{it}, where x_{it} denotes the price for asset i at date t. We assume that x_t has a factor structure[1] and can therefore be represented as the sum of a common and an idiosyncratic component; we model price comovements accordingly using the following linear model

$$x_t = \mu + \Lambda f_t + \xi_t \tag{5}$$

where μ is constant, f_t is a $r \times 1$ vector of r common factors that capture common sources of variation among prices. The r factors are loaded via the coefficients in Λ that determine how each price series reacts to the common shocks. Lastly, ξ_t is a $N \times 1$ vector of idiosyncratic shocks that capture price-specific variability or measurement errors. Both the common factors and the idiosyncratic components are assumed to be zero mean processes.

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

$$f_t = \Phi_1 f_{t-1} + \ldots + \Phi_p f_{t-p} + \varepsilon_t \tag{6}$$

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

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

matrix Q.

We further assume that the idiosyncratic component is a collection of independent univariate autoregressive processes:

$$u_{i,t} = \alpha_i u_{i,t-1} + e_{i,t} \tag{7}$$

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

The model in equations (5) to (7) is an approximate dynamic factor model (DFM) where we explicitly model the dynamic of both the common and the idiosyncratic component allowing for the latter to display some degree of autocorrelation while we rule out pairwise correlation between assets assuming that all the co-variation is accounted for by the common component. This assumption might be interpreted as being particularly stringent in presence of high degrees of heterogeneity in the data, nevertheless, it does not compromise the estimation of the model since consistency of the ML estimator is proven even under misspecification as it will be further discussed later in the paragraph.

In order to distinguish between comovements at different levels of aggregation we allow the vector of common shocks to include both aggregate shocks that affect all prices and shocks that affect many but not all prices. In particular, following Banbura et al. (2010) we assume the common component to be partitioned into a global and several region or type specific factors to account for comovements which are proper to a specific market and, most importantly, to disentangle sources of variation that are widespread and common to *all* price series regardless of the geographical distribution or the underlying asset type. We will denote the latter as *global*.

Stated differently, we assume that each price series in x_t can be rewritten as:

$$x_{i,t} = \mu_i + \lambda_{i,G} f_t^G + \lambda_{i,M} f_t^M + \xi_{i,t} \tag{8}$$

In equation (8) $x_{i,t}$ is a function of the global factor (f_t^G) that is loaded by all the variables in x_t, of a market-specific factor (f_t^M) that is only loaded by the series in x_t that belong to the same (geographical or asset class specific) market M, and of a series-specific component.

A similar specification has been adopted by Kose (INSERT DYN CITATION HERE). They test the hypothesis of the existence of a world business cycle using a Bayesian dynamic latent factor model and discuss the relative importance of world, region and country specific factors in determining domestic business cycle fluctuations. In the context of the model in equations (5) to (7) the implementation of the block structure is achieved by imposing restrictions to the coefficients in Λ and Φ_i ($i = 1, \ldots, p$); more precisely, let the variables in x_t belong to k different markets and, without loss of generality, assume that they are ordered according to the market they refer to such that $x_t = (x_t^{M1}, x_t^{M2}, \ldots, x_t^{Mk})'$ then

$$x_t = \mu + \begin{pmatrix} \Lambda_{M1,G} & \Lambda_{M1,M1} & 0 & \cdots & 0 \\ \Lambda_{M2,G} & 0 & \Lambda_{M2,M2} & & \vdots \\ \vdots & \vdots & & \ddots & 0 \\ \Lambda_{Mk,G} & 0 & \cdots & 0 & \Lambda_{Mk,Mk} \end{pmatrix} \begin{pmatrix} f_t^G \\ f_t^{M1} \\ f_t^{M2} \\ \vdots \\ f_t^{Mk} \end{pmatrix} + \xi_t \tag{1'}$$

Moreover,

$$\Phi_i = \begin{pmatrix} \Phi_{i,G} & 0 & \cdots & 0 \\ 0 & \Phi_{i,M1} & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \Phi_{i,Mk} \end{pmatrix} \qquad Q = \begin{pmatrix} Q_G & 0 & \cdots & 0 \\ 0 & Q_{M1} & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & Q_{Mk} \end{pmatrix}$$

The setup adopted in this study differs significantly from the standard applications of the DFM in that we concentrate our attention on prices rather than returns and this implies having to take into account the fact that the elements in x_t are non stationary. If the non stationary process x_t admits a factor structure, then the source of non stationarity can be entirely pervasive, or idiosyncratic or a combination of both. Despite being an interesting question *per se*, testing for the presence of unit roots in the idiosyncratic component becomes particularly important when it comes to estimate the factors: if ξ_t is I(1), a regression of x_t on f_t would lead to inconsistent estimates of Λ and ξ_t even if f_t were observed. The elements in f_t, on the other hand, can be stationary, non stationary or both[2]. In this framework we allow both the elements in f_t and ξ_t to display non stationarity by combining the DFM structure with the PANIC (Panel Analysis of Nonstationarity in Idiosyncratic and Common components) approach developed by Bai and Ng (2004)[3].

Consider again the model in (5) where x_t is I(1) and let $\tilde{z}_t = \Delta z_t$ denote the first difference for any variable z_t, then consistent estimates of the common factors in f_t can be obtained by cumulating the factors estimated from the stationary, first-differenced model:

$$\tilde{x}_t = \Lambda \tilde{f}_t + \tilde{\xi}_t. \tag{9}$$

In particular, $\hat{f}_t = \sum_{s=1}^{T} \hat{\tilde{f}}_s$ and $\hat{\xi}_t = \sum_{s=1}^{T} \hat{\tilde{\xi}}_s$. Bai and Ng (2004) show that $\hat{f}_t$ is a consistent estimate of f_t up to a scale and an initial condition f_0.

We estimate the approximate DFM using maximum likelihood as in Doz et al. (2006); Banbura et al. (2010); Reis and Watson (2010)[4]. 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 smoother at each iteration (Engle and Watson, 1981). The algorithm is initialized using principal component estimates of the factors that are proven to provide a good approximation of the common factors when the cross sectional dimension is large[5].

Before proceeding with the estimation, the (log) asset price series are suitably transformed to achieve stationarity; also, the variables are demeaned and are all normalized to have unit

[2]Let $r_0 \leq r$ be the number of stationary factors; if $r = 1$ then standard univariate ADF tests can be applied to test if the common factor is a unit root process, conversely, if $r > 1$ then the method developed in Bai and Ng (2004) can be applied to determine $r_1 = r - r_0$, the number of independent stochastic trends underlying the r common shocks.

[3]Similar approaches have been followed by Eickmeier (2009) to study the sources of comovements and heterogeneity in the euro area and by Luciani and Veredas (2011) in the context of a model for large panel of long-memory processes.

[4]Doz et al. (2006) discuss consistency of the maximum likelihood estimator for a large approximate factor model. They show that traditional factor analysis is feasible in large cross-sections and that consistency is achieved even if the underlying data generating process is an approximate factor model; in particular they show that as $N, T \to \infty$ the expected value of the common factors converges to the true factors along any path.

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

variance to account for differences in the measurement units; the normalization also prevents variables displaying larger variability to influence the estimation of the factors. The optimal number of VAR lags (p in (6)) is selected using the Likelihood Ratio test and is equal to 1.

To ensure consistency with our theoretical formalization, the model is applied to a vast collection of prices of different risky assets traded on all the major global markets. The geographical areas covered are Europe - further decomposed into Euro area and UK -, the US and Asia, with the latter combining Japan as well as South Korea, Singapore, Hong Kong and Taiwan. Stacked to this set are corporate bonds data and all major commodities price series; we exclude precious metals from our set.

All price series are taken at monthly frequency using end of month values to reduce the noise in daily figures while preserving the long run characteristics of the series. The time span covered is the twenty years period from January 1990 to December 2010. In order to select the series that are included in the global set we proceed as follows: first for each market we pick a representative market index and all of its components as of the end of 2010, then we keep only those that have continuously been traded during the entire time span in order to produce a balanced panel. The resulting dataset has an overall cross-sectional dimension of $N = 428$. Apart from proper geographical areas, in the block structure in equation $(1')$ we treat the last two categories, corporate bonds and commodities, as separate markets; this results in a specification where the total number of markets considered in the analysis is equal to 6.

We fit to the data a model with one global and one specific factor per market. The choice is motivated by a set of results which we obtain using both formal tests and a number of different criteria. The test that we implement is the one developed by Onatski (2009), where the null of $r-1$ factors is tested against the alternative of r common factors. We complement this result with the information criteria in Bai and Ng (2002) where the residual variance of the idiosyncratic component is minimized subject to a penalty function increasing in r, and the percentage of variance that is explained by the i-th eigenvalue (in decreasing order) of both the covariance matrix and the spectral density matrix. The outcomes for the global set are collected in table 1. According to the figures shown, the largest eigenvalue alone, in both the time and frequency domain, accounts for more than 60% of the variability in the data; similarly, the IC criteria reach their minimum when one factor is implemented while the p-values collected in the last column suggest the inclusion of one to two common factors. A very similar picture emerges from the same exercise performed over the six partitions of the global set where again the figures suggest the presence of one common factor only; results are not reported here but are available upon request.

Table 1: NoF (global set)

	Global Set					
	% covariance	% spectral	Bai Ng criteria			Onatski
r	matrix	density	IC1	IC2	IC3	test
1	0.703	0.635	-0.149	-0.146	-0.159	0.033
2	0.134	0.136	-0.117	-0.110	-0.136	0.024
3	0.063	0.069	-0.085	-0.076	-0.114	0.879
4	0.033	0.043	-0.052	-0.041	-0.092	0.488
5	0.022	0.029	-0.020	-0.006	-0.070	0.155
6	0.014	0.019	0.012	0.029	-0.048	0.287
7	0.008	0.013	0.043	0.064	-0.026	0.651
8	0.006	0.009	0.076	0.099	-0.004	0.652
9	0.003	0.007	0.108	0.134	0.018	0.763

Note: For 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 ICs criteria in Bai and Ng 2002 and the p-value for the Onatski test where the null of $r-1$ common factors is tested against the alternative of r common factors.

3.1 The global factor

The estimated global common factor is plotted in Figure 1. Recall from previous sections that the common factors are obtained via cumulation and are therefore consistently estimated only up to a scale and an initial value f_0 that, without loss of generality, we set to be equal to zero. This implies in practical terms that positive and negative values displayed in the chart cannot be interpreted as such and that they do not convey any specific information *per se*; rather, it is the overall shape, the points in time at which it peaks and the turning points that are of interest and deserve particular attention.

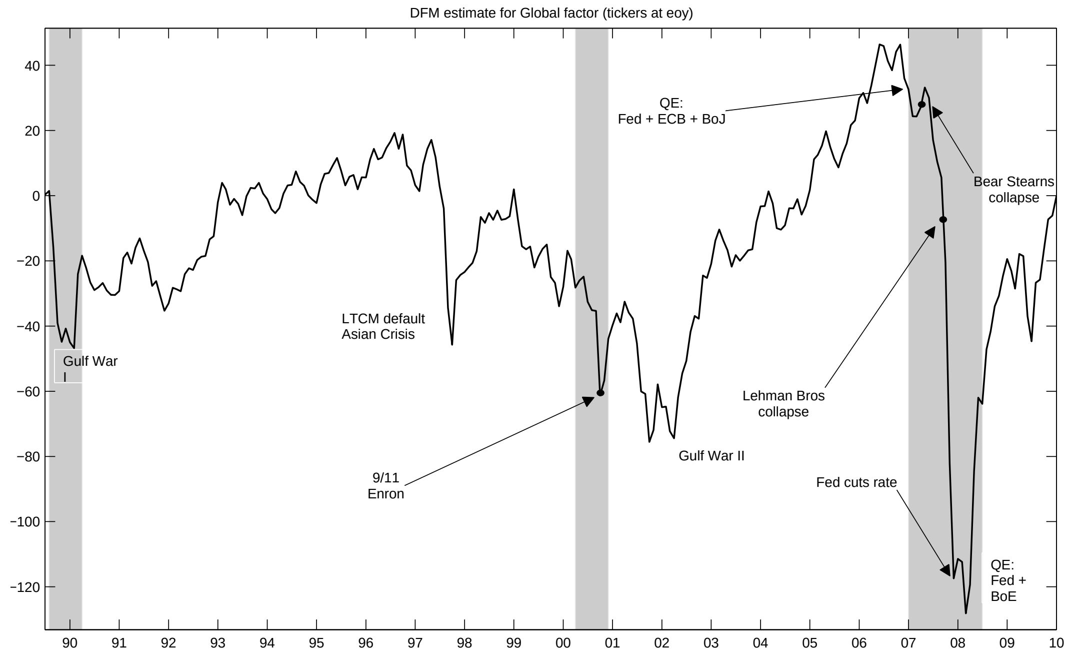

Figure 1: Estimate of the global factor.

First of all, the factor is consistent with the recession periods identified by the NBER that fall within the time window considered. These go from July 1990 to March 1991, March 2001 to November 2001 and December 2007 to June 2009. In all the three recession episodes the index exhibits sharp declines followed by equally abrupt changes in direction, in particular, the timing of the downward spikes within the recession periods is consistent with major events taking places such as the Gulf War starting from the second half of 1990, 9/11 and the first quarter of 2009 when the most recent financial crisis reached its climax. Overall, the index enjoys an upward trend from the early Nineties until mid 1998 when both the LTCM bailout and the East Asian Crisis revert the increasing path that was presumably due, at least in part, to the building up of the *dot-com* bubble. Such downward trend is inverted starting from the beginning of 2003 with the index increasing at sustained speed until the beginning of the third quarter of 2007 when, triggered by the the collapse of the subprime market, the first signals of increased vulnerability of the financial markets become visible leading to an unprecedent decline that has only partially recovered since then.

Although all price series included in the global set are taken in US dollars, we verify that the shape of the global factor is not influenced by this choice by repeating the same exercise on the same global set where, instead, we leave the currency in which the assets are originally traded in unchanged. The resulting global factor is very much alike the one constructed from the dollar denominated set both in terms of overall shape and of peaks and troughs that perfectly coincide throughout the time span considered; the two global factors are plotted against one another in figure 13 in Appendix A[6].

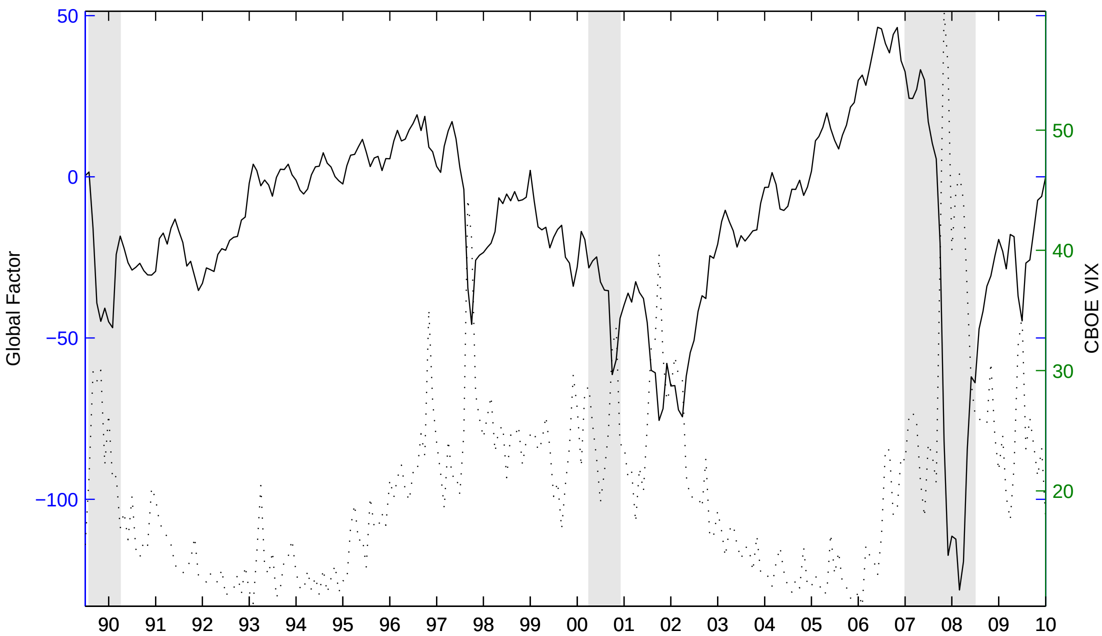

Figure 2: Global Factor vs VIX index.

[6]The six regional factors extracted from the global set are also reported in the appendix in figures 14 and 15.

In Figure 2 the global index is plotted against the end of month readings of the CBOE volatility index (VIX). The index measures the implied volatility of highly liquid SPX (S&P 500) index options and is specifically constructed to reflect the market's risk-neutral expectation of future market variance in a pure model-free fashion[7]; it is also typically used as a proxy for market uncertainty.

The degree of comovement between the estimated global factor and the VIX index is strikingly high; especially after the late Nineties. Whenever the global factor exhibits pronounced peaks or changes in direction these tend to coincide with peaks in the market implied volatility. Particularly significant in this respect are the episodes of increased turbulence where markets overall were subject to abnormal stress. Recall from the theoretical setup outlined in this paper that the price of risky assets, apart being naturally a function of asset specific characteristics, is also determined by the degree of risk aversion of global banks which, in turn, is intimately related to the overall degree of uncertainty perceived in the market. Taking this into account leads to an almost natural interpretation of the estimated global factor as an index capturing the risk associated to global asset markets, in particular we will interpret the global risk factor as capturing the degree of risk appetite of VaR-constrained global investors. We exploit the empirical consequences of such interpretation in the following sections where we analyze the attitude toward risk of leveraged global banks and the interaction between price and quantity of risk and monetary policy.

[7]The VIX was originally calculated using the Black-Scholes formula on S&P 100 options; subsequently, in September 2003, the CBOE introduced a new model-free VIX index based instead on S&P 500 options. Historical data and calculation details are available at `http://www.cboe.com/micro/VIX/vixintro.aspx`

4 Returns and leverage of Global Banks

Within the theoretical framework defined in previous sections, the expected excess return of a global bank portfolio in our economy is equal to:

$$E_t(\mathbf{x}_t^{B\prime}\mathbf{R}_{t+1}) = \beta_t^{BW}\Gamma_t$$

where β_t^{BW} is a measure of risk loading on the world market and Γ_t is our effective aggregate risk aversion parameter. To investigate global banks behavior and their attitude toward risk we follow Chen and Rey (INSERT DYN REFERENCE HERE) and put together a panel of monthly return indices for 166 financial institutions in 20 countries over the years from 2000 to 2010. From the universe of world banks and financial institutions we select those that are big enough to be presumably involved in cross border activities, and thus active market makers, and whose geographical location roughly matches the main markets in which the assets used to estimate the global factor above are originated or most actively traded.

Taking as a reference the outstanding amount of total assets as of December 2010, we also identify a subset of 55 very large banks of which 21 have been classified as Globally Systemically Important Financial Institutions (*G-SIFIs*). The list of G-SIFIs, defined as those "financial institutions whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity", has been compiled by the Financial Stability Board together with the Basel Committee of Banking Supervision in November 2011 to isolate global financial services groups that are systemically relevant[8]. The relevance of each institution has been measured according to five different criteria that concern size, level of complexity, the degree of interdependence with the financial system as a whole, and the range of cross-border activities; also, among the criteria, the regulators measured the amount of services provided exclusively by these subjects or that, in other words, could not easily be replaced by other banks in the event of failure. A complete list of institutions included in our set is in Table

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

B.1 reported in Appendix B; return indices and total asset data are from Bloomberg. Figures 3 and 4 report the correlation between beta and returns calculated over the entire sample and the big banks subsample respectively; in figure 4 the labeled dots correspond to the G-SIFIs defined above and for both samples we use August 2007 as a breaking point to distinguish between pre and post crisis periods. In order to compute the banks betas and thus their loading on global risk we have used our global factor which, by construction, is effectively a synthetic global market index.

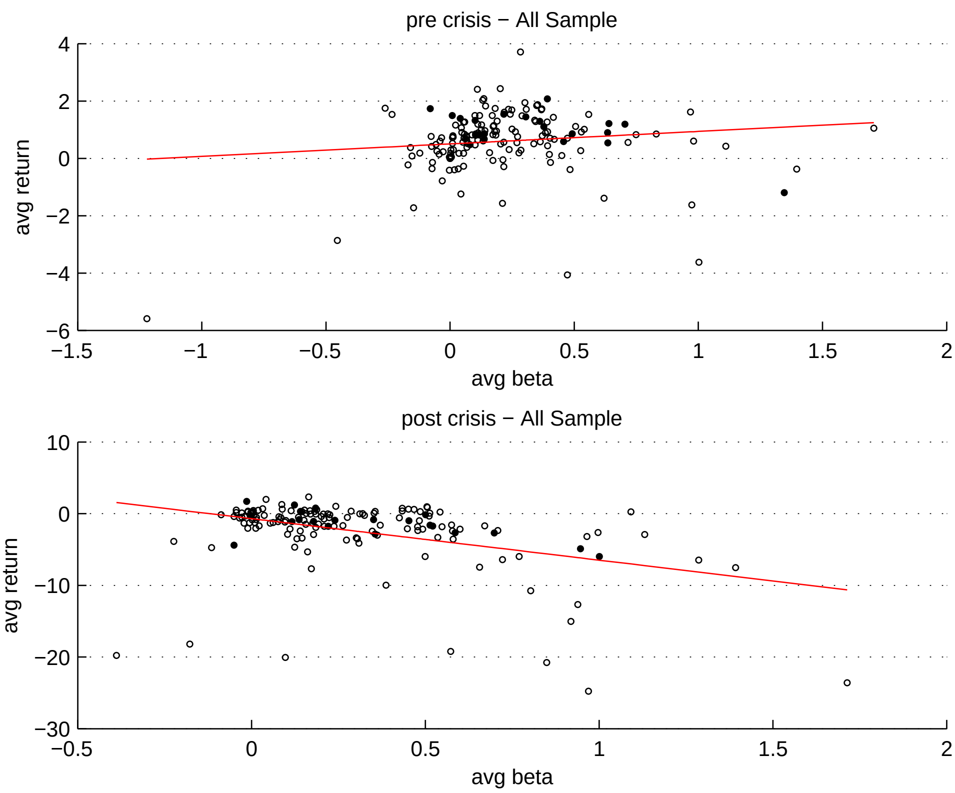

Figure 3:

Results suggest that global banks have gone through an initial phase in which they were building up leverage and then reverted abruptly after the beginning of the crisis; this

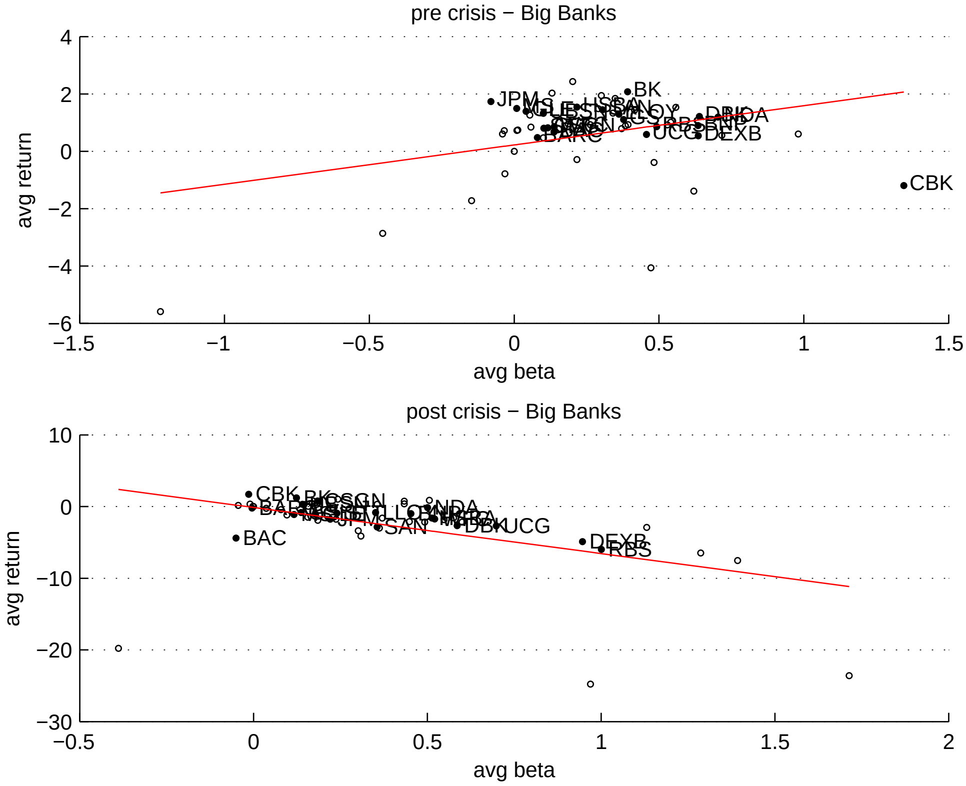

Figure 4:

inversion being particularly marked for the big and systemically relevant institutions for which the increase in leverage is much stronger during the pre crisis period. In a context in which global banks are risk neutral and subject to a VaR constraint Shin and Adrian and Shin (INCLUDE REFERENCES HERE) show that if the constraint binds all the times then banks will adjust their positions depending on the perceived risk so that their VaR does not change; this mechanism implies that even when risk is low - or perceived as such - they will increase their exposure in a way that ensures that their probability of default remains unchanged. Using data on quarterly growth rates of both total assets and leverage Adrian and Shin show that in fact banks, and particularly broker-dealers, react to stronger balance sheets in a systematically different way with respect to households and other financial subjects; specifically, they actively manage their leverage by adjusting their demand for assets in a way that makes leverage procyclical or, in other words, increasing in the size of their balance sheets. Building on this result we provide further evidence of leverage procyclicality extending the analysis to our sample of 166 banks and report our findings in figures (5) to (7). In figure (5) for each of the systemically risky financial institutions the quarterly growth of assets is plotted against the quarterly growth of their leverage ratio computed as total assets over equity; to enhance readability, the 45 degree line is also added to each plot. The emerging pattern is clear and consistently reproduced in each of the subplots: leverage grows together with the size of banks balance sheets in a way that confirms the relatively passive role that is assigned to equity. These results go beyond the findings of Adrian and Shin in showing that leverage procyclicality is not specific to US broker-dealers but is in fact a widely adopted strategy among global investors worldwide; figure (5) shows how European global banks were also actively managing their leverage by adjusting its level to the growing (prior to Q2-2008) size of their balance sheets. When, after the Lehman episode, the environment started to change and the depth of the crisis became more visible, major global banks worldwide reacted with a sudden change in direction that involved massive deleveraging operations. This fueled and amplified the drop that asset prices experienced across all financial markets during 2008.

Figures (6) and (7) collect the evidence recorded looking at the aggregate total asset and leverage ratio of those institution in our sample that are classified as Commercial Banks and Capital Markets according to GICS (Global Industry Classification Standard, see table (B.1) in the Appendix for details). The time span covered is 2005-Q1 to 2010-Q4 due to data availability, also, we dropped from the sample institutions for which data series did not cover at least 80% of the time window under analysis. The difference between the two plots confirms the peculiarity of the behavior attributable to financial institutions operating in capital markets; in particular, Figure 6) shows that there is no evidence of commercial banks worldwide adjusting their leverage according to the size of their balance sheets and that procyclical leverage is a feature specific to global investors.

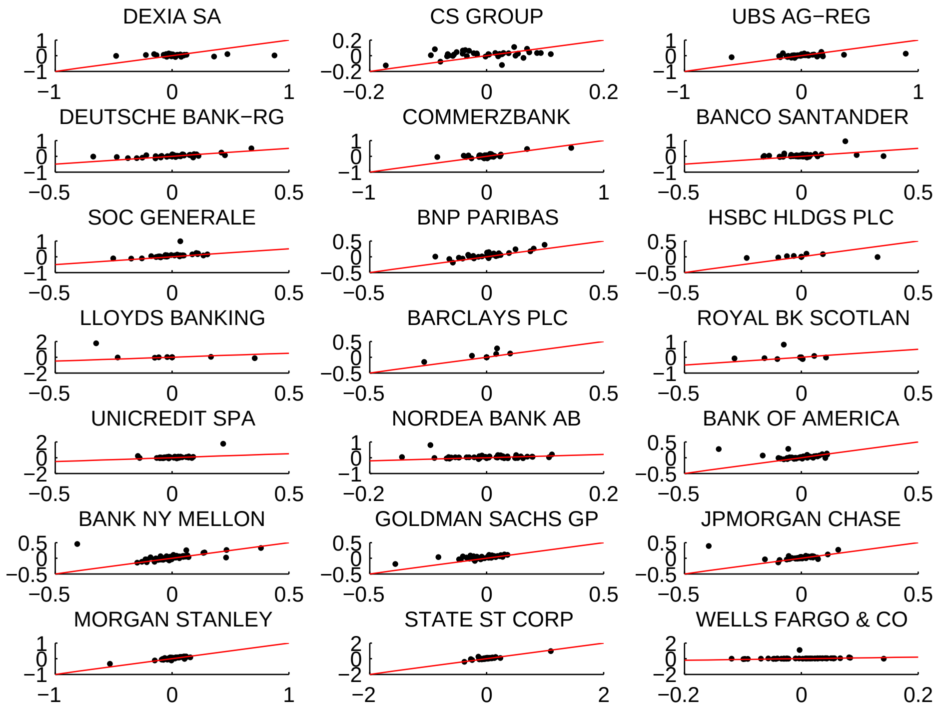

Figure 5:

The positive association between the size of balance sheets and leverage documented above, combined with the evidence of a rather stable level of total equity, creates room for a potential feedback effect that magnifies the consequences of shocks to asset prices making this the core mechanism behind the process of creation and destruction of global (private) liquidity[9]. An increase in asset prices strengthens banks balance sheets reducing their leverage; if banks privilege a strategy that maintains leverage at a fixed level, they will react to the price shock enlarging the size of their balance sheets by increasing their demand for assets; this, in turn, will push asset prices further reinforcing the cycle. Clearly, these forces will go in opposite direction during a downturn.

Global banks through leveraging and deleveraging effectively influence funding conditions

[9]Private liquidity here is to be intended as opposed to global official liquidity created by national central banks that are in principle capable of providing potentially unlimited funding sources through instruments like foreign exchange reserves and swap lines.

for the entire financial system and ultimately for the broader international economy. Depending on their ability and willingness to take on risk and perform maturity transformation, financial institutions can amplify monetary stimuli introduced by central banks. In particular, easier funding or particularly favorable credit conditions can translate into an increase in liquidity and credit growth, reduction of risk premia and run up of asset prices. Crucial in this process is the attitude towards risk of international financial players that, in turn, determines their willingness to provide cross border or foreign currency financing (CGFS 2011 PAPER - INSERT REFERENCE HERE). Following this reasoning, the results in this section suggest that prior to the beginning of the crisis the aggregate level of risk appetite of global investors was high and increasing; this combined with expanding sized of balance sheets induced banks to leverage up by increasing exposures and creating particularly favorable funding conditions that lead to increasing liquidity through gross international capital flows and cross border banking. When, on the other hand, in the second half of 2007 the financial sector began to shake after the subprime collapse episode, the cycle reverted resulting in the erosion of private liquidity and the sharp decline in asset prices.

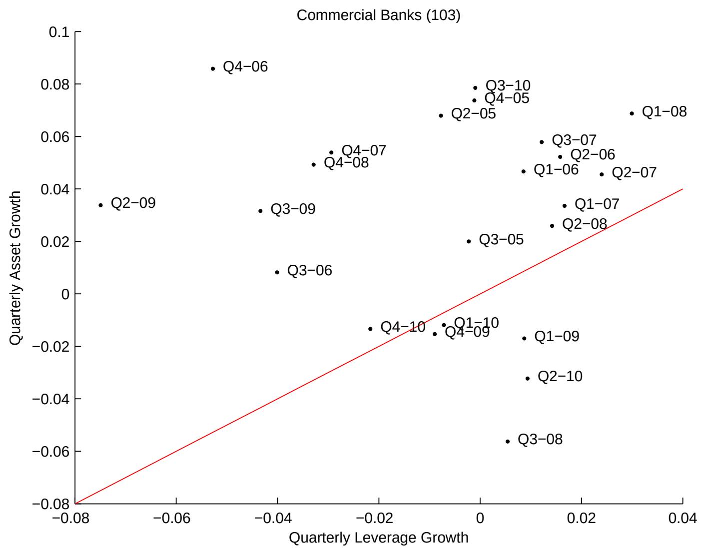

Figure 6:

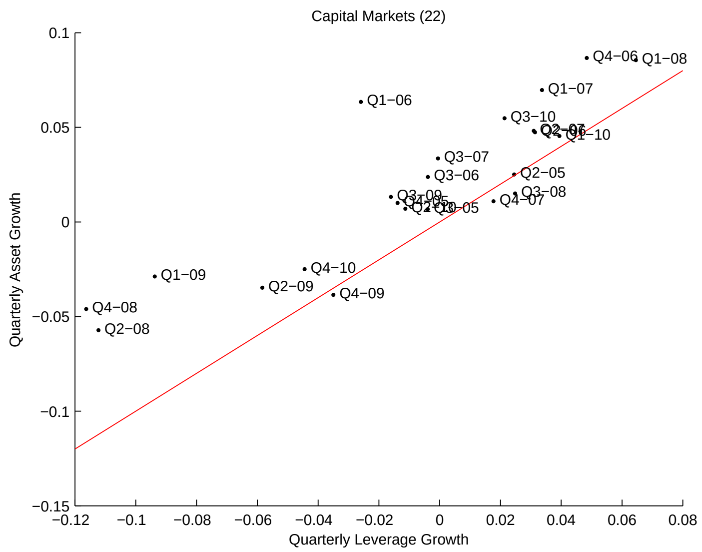

Figure 7:

5 World asset prices and monetary policy

In Section 3 we have documented a strong comovement between the CBOE VIX index and the global factor estimated from our panel of world risky assets that suggested the possibility of interpreting the latter as an index carrying information on both market volatility and market sentiment. In this section we explore this concept further and study the impact that changes in global investors' risk appetite have on global market uncertainty and monetary policy; also, we explore the effects of shocks propagation from the financial markets to the real side of the economy. We present our results in the form of impulse response functions from two different VAR specifications: the first one is effectively a factor-augmented VAR where the global risk factor is stacked to a vector containing business cycle indicators, a monetary policy instrument and a measure of global market variance; the second one is in fact a complementary specification in which we decompose the global risk factor into a component primarily driven by market variance and a residual index of aggregate risk aversion. In our first specification we run a 3-lag VAR on monthly US industrial production[10], US Consumer Price Index, the effective Fed Funds Rate, a measure of global market variance and our global risk factor. In this exercise both industrial production index and cpi are taken in deviation of HP trend ($\lambda = 129600$) following Bloom (INSERT DYN REFERENCE HERE); also, we scale the global risk factor to have the same standard deviation of the measure of global variance such that the VAR shocks to market realized variance and investors risk appetite are of comparable size. In this specification we let the VAR automatically separate the effects of market uncertainty from risk appetite ordering the global risk factor as the last variable of our VAR. In this context global market-related variables are assumed to respond within the month to changes to the business cycle and to the monetary policy stance; the use of US fed fund rates reinforces the primary role of US dollars as main currency underlying financial transactions worldwide.

We start by constructing a measure of global realized variance. In standard empirical fi-

[10]

nance applications daily measures of realized variance are built summing up squared intraday returns sampled at very high frequency, usually in the order of five minutes, that are shown to provide a very accurate estimation of the true, unobserved, return variation (Andersen et al 2001a, 2001b, Barndorff-Nielsen&Sheppard 2002, Meddahi 2002) INSERT DYN REFERENCE HERE. Borrowing from this literature we construct a measure of monthly global realized variance using squared daily returns of the MSCI all countries index to match the sampling frequency of the estimated global factor; we use the MSCI realized variance as a proxy for global market variance following the evidence on high degree of comovement in large panels of realized volatilities that has been documented in recent studies (Barigozzi et al 2011 among others INSERT DYN REFERENCE HERE).

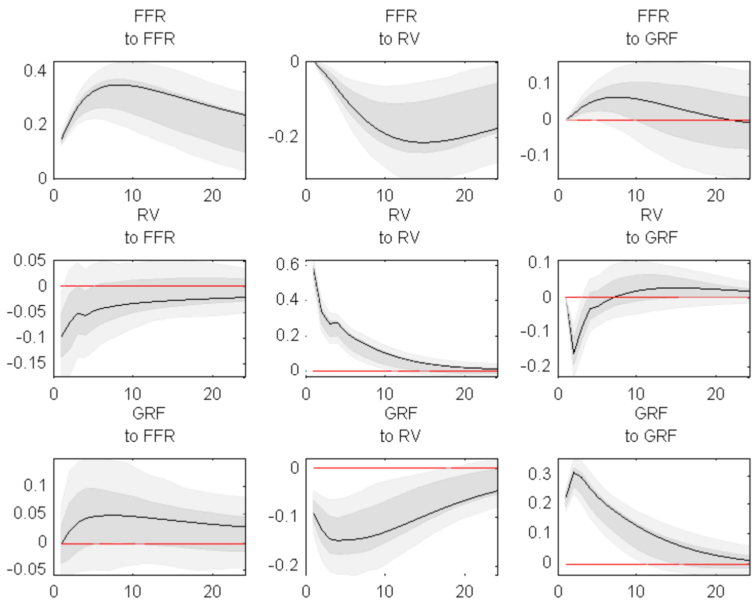

Figure 8:

The top panel of Figure 10 below reports the annualized values of the global realized volatility over the years from 1990 to 2010 while the residual of the projection of the global

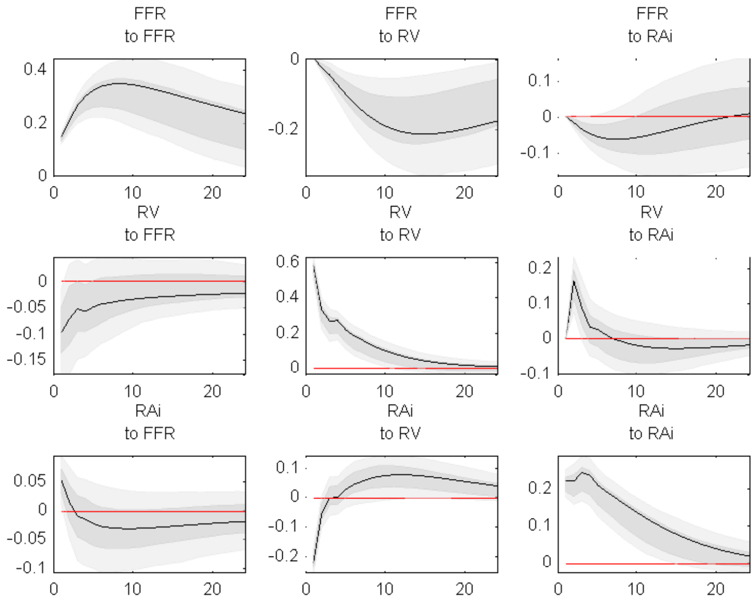

Figure 9:

factor on the realized variance for the same time span is in the bottom panel. According to our model, this difference is meant to capture comovements among world asset prices that are not accounted for by market uncertainty and are instead related to the overall degree of risk aversion in the market. The construction of our proxy for aggregate risk aversion is modeled along the lines of Bollerslev et al 2009 and Bekaert et al 2011 (INSERT DYN REFERENCES HERE) that estimate variance risk premia as the difference between a measure for the implied variance - the squared VIX - and an estimated physical expected variance which is primarily a function of realized variance. Consistent with the findings in Section 4, the plot in Figure 10 shows how risk appetite of global players in the international financial market started increasing during the years prior to the recent financial crisis and how it remained persistently high up until 2009. This, combined with procyclical leverage and favorable credit conditions, contributed to a great extent to the run up of asset prices and the build up of systemic risk that eventually led to the crash.

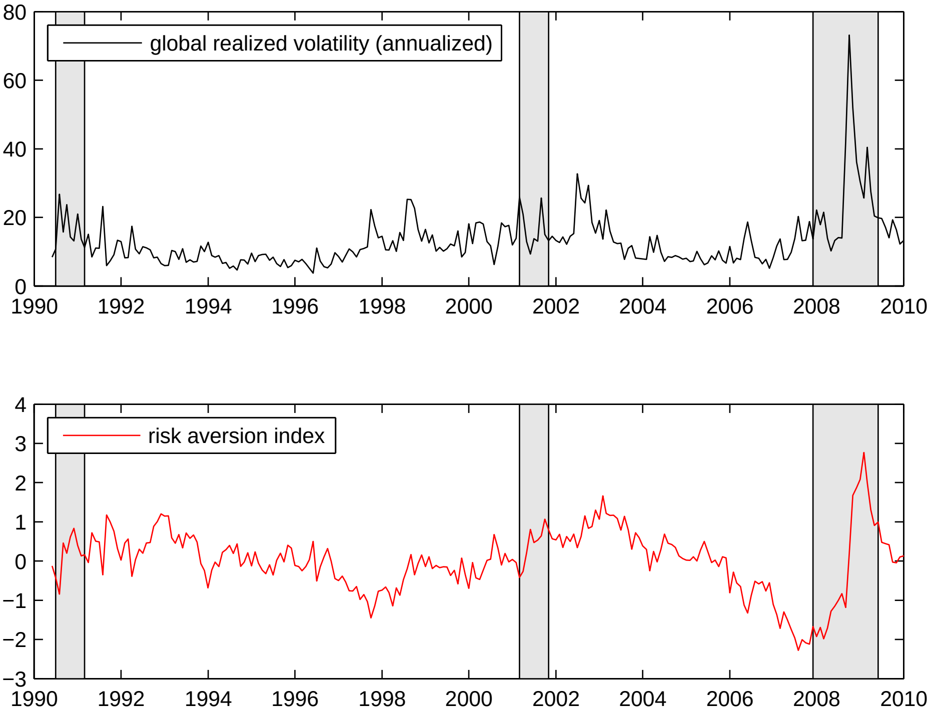

Figure 10:

To analyze the interaction between monetary policy and risk, measured both in terms of market uncertainty and risk aversion, we start by setting up a three variables VAR following the ordering in Bekaert et al 2011 (INSERT DYN REF HERE) where effective Fed funds rates (FFR_t) are followed by our index of risk aversion (RAi_t) and (log) global realized variance (RV_t). We use a three lag VAR to capture dynamics at quarterly frequency. Impulse response functions are reported in Figure 12 where bootstrapped confidence intervals are computed using 1000 replications; light and dark gray shaded areas correspond to 95 and 86% confidence intervals respectively. A positive shock to FFR is followed in our model by a significant reduction in global market uncertainty and a positive, all though short lived, response of aggregate risk aversion; put differently, lax monetary policy would lead in our setup to an increased willingness to take on risk and a consequently high market turbulence confirming in this respect the results in Bekaert et al 2011. On the other hand, the effects of increased market instability, measured in terms of higher realized variance, tend to be both significant and very persistent; the sharp reduction in risk appetite remains low for at least two quarters before eventually starting to revert to its original level, with the effect becoming negligible only after 20 periods. Similarly persistent, but with opposite sign, is the response of nominal interest rate; in contrast to this result, Bekaert et al 2011 using real interest rate measured as the difference between Fed fund target rate and CPI inflation, find that the effect of uncertainty on the monetary policy stance is still negative but rather weak.

Results plotted in figures **??** and **??** are from a richer specification where we augment our three variables VAR with the log of monthly industrial production index as a business cycle indicator and CPI inflation rate; we treat these two variables as slow moving compared to the ones in the benchmark VAR and therefore order them first. The inclusion of these two variables does not alter the structure of responses discussed above, testing *de facto* the robustness of our previous results; furthermore, it allows us to disentangle the effects that both market uncertainty and aggregate risk aversion have on real activity and, on the other hand, if and how a shock to real activity affects prices and quantity of risk. Figure **??** displays the response of IP to a positive shock to our risk aversion index (panel a) and to global market variance (panel b). In both panels the response to a positive shock to Fed funds rate (dashed line) is added for comparison; shaded areas are 86% confidence intervals.

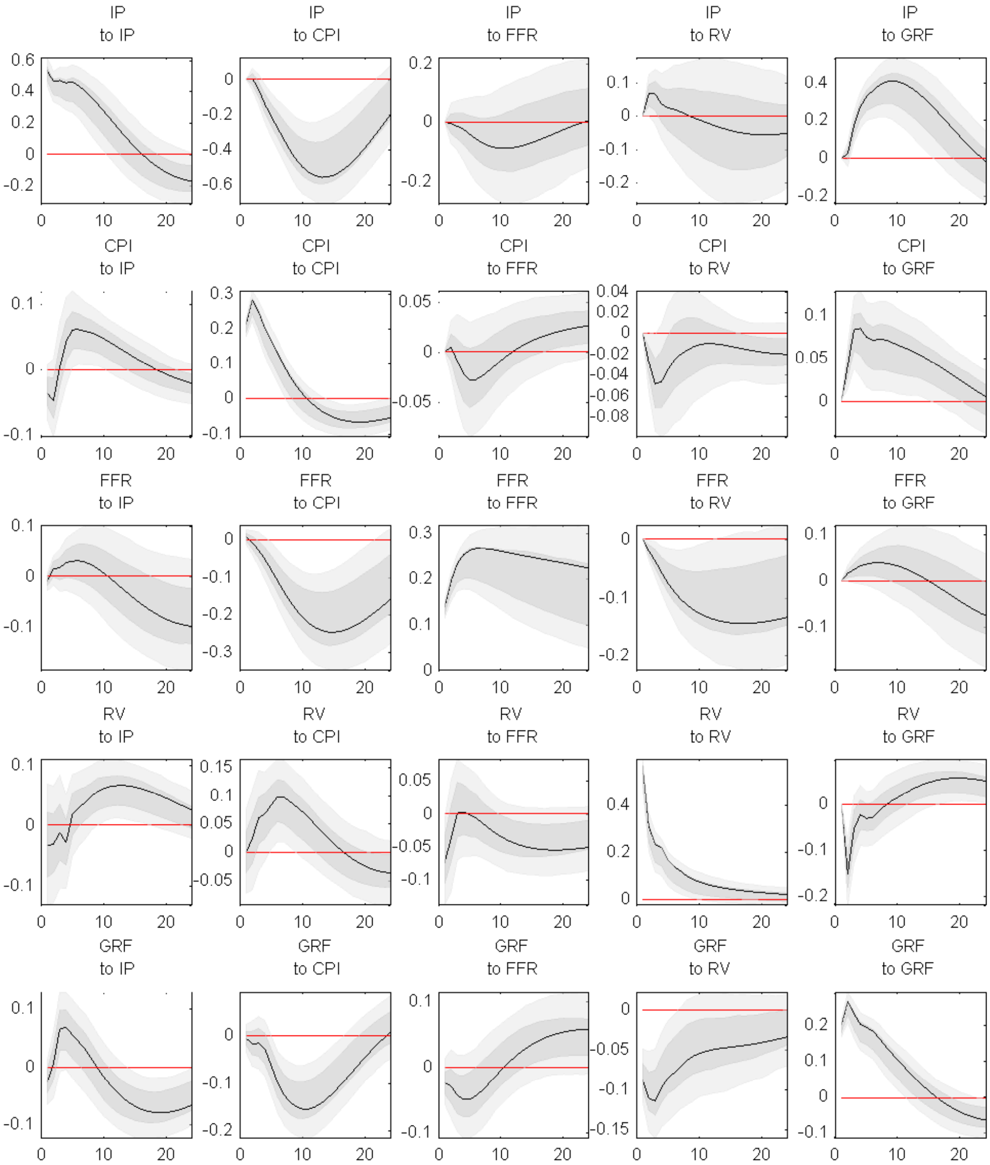
IP to IP
IP to CPI
IP to FFR
IP to RV
IP to GRF
CPI to IP
CPI to CPI
CPI to FFR
CPI to RV
CPI to GRF
FFR to IP
FFR to CPI
FFR to FFR
FFR to RV
FFR to GRF
RV to IP
RV to CPI
RV to FFR
RV to RV
RV to GRF
GRF to IP
GRF to CPI
GRF to FFR
GRF to RV
GRF to GRF

Figure 11:

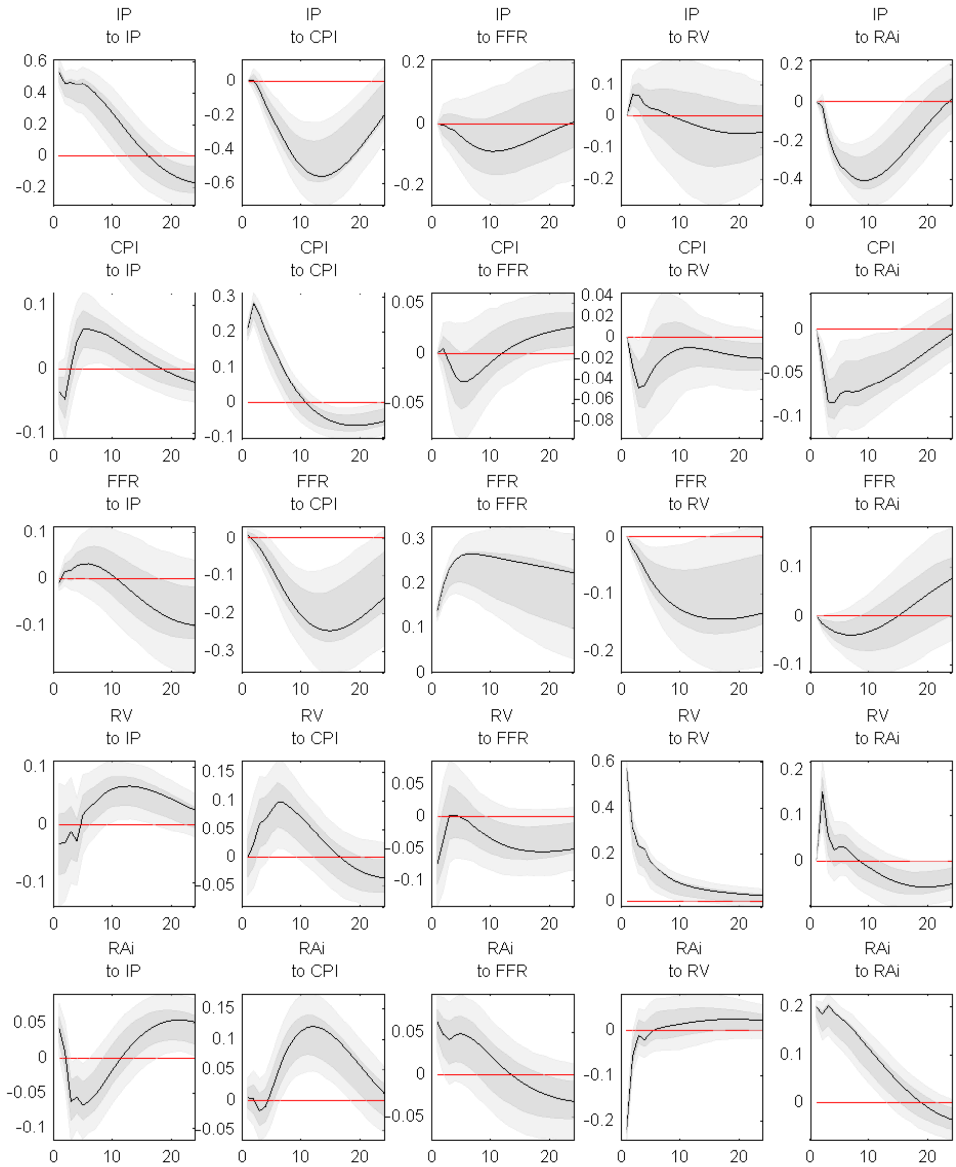
IP to IP
IP to CPI
IP to FFR
IP to RV
IP to RAi
CPI to IP
CPI to CPI
CPI to FFR
CPI to RV
CPI to RAi
FFR to IP
FFR to CPI
FFR to FFR
FFR to RV
FFR to RAi
RV to IP
RV to CPI
RV to FFR
RV to RV
RV to RAi
RAi to IP
RAi to CPI
RAi to FFR
RAi to RV
RAi to RAi

Figure 12:

6 Conclusion

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A Other Plots

A.1 usd vs lc

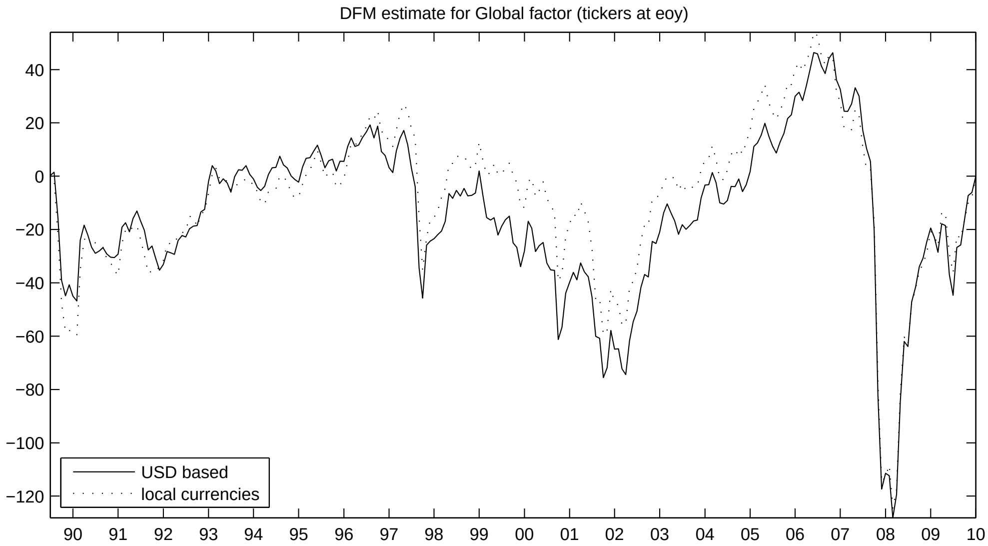

Figure 13:

A.2 regional factors

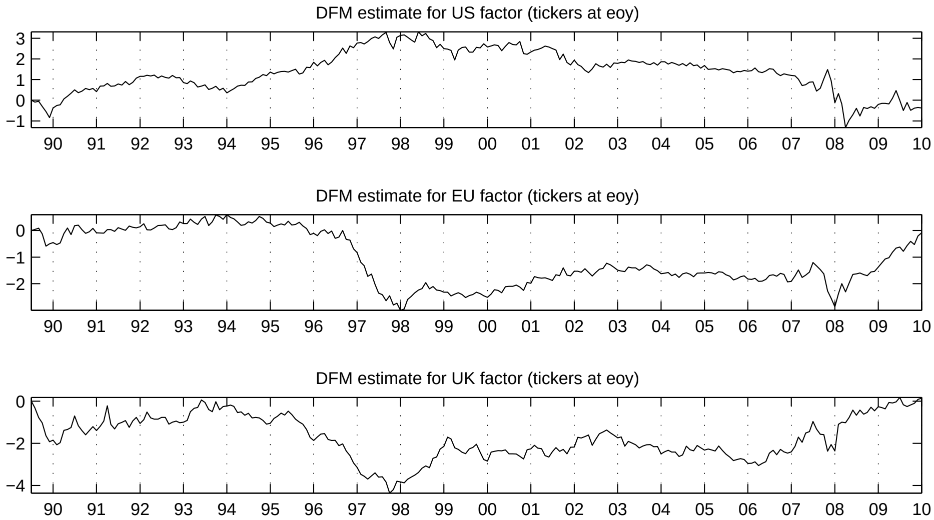

Figure 14:

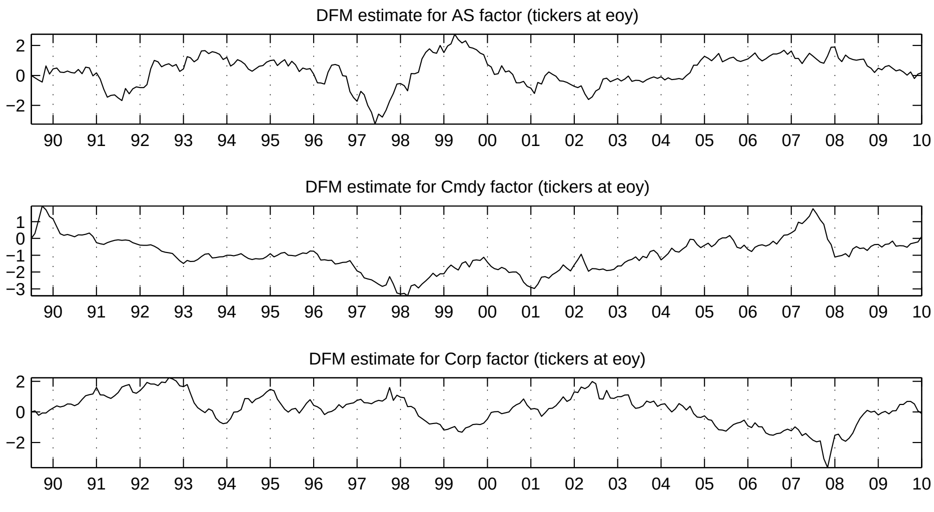

Figure 15:

B Global Banks

Table B.1: **List of Financial Institutions included in the dataset**

ISIN code	Bank Name	Country	Big	G-SIFI
AT0000625108	Oberbank AG	Austria		
AT0000652011	Erste Group	Austria	✓	
AT0000755665	Oesterreichische Volksbanken AG	Austria		
BE0003565737	KBC Group	Belgium	✓	
BE0003796134	Dexia	Belgium	✓	✓
CA0636711016	Bank of Montreal	Canada	✓	
CA0641491075	SCOTIABANK	Canada		
CA1360691010	Canadian Imperial Bank of Commerce	Canada	✓	
CA13677F1018	Canadian Western Bank	Canada		
CA4369131079	Home Capital Group Inc	Canada		
CA4495861060	IGM Financials Inc	Canada		
CA51925D1069	Laurentian Bank of Canada	Canada		
CA6330671034	National Bank of Canada	Canada	✓	
CA7800871021	Royal Bank of Canada	Canada	✓	
CA8911605092	Toronto Dominion Bank	Canada	✓	
CH0012138530	Credit Suisse Group	Switzerland	✓	✓
CH0012335540	Vontobel Holding AG-Vontobel Group	Switzerland		
CH0018116472	Bank Coop AG	Switzerland		
CH0024899483	UBS	Switzerland	✓	✓
DE0005140008	Deutsche Bank	Germany	✓	✓
DE0008023227	Landesbank Berlin Holding	Germany	✓	
DE0008032004	Commerzbank	Germany	✓	✓
DK0010274414	Danske Bank	Denmark	✓	
DK0010307958	Jyske Bank A/S (Group)	Denmark		
ES0113211835	BBVA	Spain	✓	
ES0113440038	BANESTO	Spain		
ES0113679I37	Bankinter SA	Spain		
ES0113790531	Banco Popular Espanol	Spain	✓	
ES0113900J37	Banco Santander	Spain	✓	✓
ES0113980F34	Banco de Valencia SA	Spain		
FR0000031684	Paris Orlans SA	France		
FR0000120685	Natixis	France		
FR0000130809	Societe Generale	France	✓	✓
FR0000131104	BNP Paribas	France	✓	✓
GB0005405286	HSBC Holdings	UK	✓	✓
GB0008706128	Lloyds Banking Group	UK	✓	✓
GB0031348658	Barclays	UK	✓	✓
GB0033872168	ICAP Plc	UK		
GB00B7T77214	Royal Bank of Scotland	UK	✓	✓
GRS003013000	National Bank of Greece	Greece	✓	
GRS006013007	Emporiki Bank of Greece S.A.	Greece		
GRS015013006	Alpha Bank AE	Greece		
IE0000197834	Allied Irish Banks	Ireland	✓	
IE0030606259	Bank of Ireland	Ireland	✓	
IE00B59NXW72	Irish Life & Permanent	Ireland	✓	
IT0000062957	Mediobanca SpA	Italy		

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Table B.1 – continued from previous page

ISIN code	Bank Name	Country	Big	G-SIFI
IT0000064359	Credito Bergamasco	Italy		
IT0000064482	Banca Popolare di Milano SCaRL	Italy		
IT0000072618	Intesa Sanpaolo	Italy	✓	
IT0001005070	Banco di Sardegna SpA	Italy		
IT0001070769	Credito Artigiano	Italy		
IT0001334587	Banca Monte dei Paschi di Siena	Italy	✓	
IT0004781412	Unicredit	Italy	✓	✓
JP3105040004	Aiful Corporation	Japan		
JP3107600003	Akita Bank Ltd	Japan		
JP3108600002	Acom Co Ltd	Japan		
JP3152400002	Bank of Iwate Ltd	Japan		
JP3175200009	Oita Bank Ltd	Japan		
JP3194600007	Bank of Okinawa	Japan		
JP3199000005	Orient Corporation	Japan		
JP3200450009	Orix Corporation	Japan		
JP3207800008	Kagoshima Bank Ltd	Japan		
JP3271400008	Credit Saison Co Ltd	Japan		
JP3276400003	Gunma Bank Ltd	Japan		
JP3351200005	Shizuoka Bank	Japan	✓	
JP3352000008	77 Bank	Japan		
JP3388600003	Jaccs Co Ltd	Japan		
JP3392200006	Eighteenth Bank	Japan		
JP3392600007	Juroku Bank Ltd	Japan		
JP3394200004	Joyo Bank Ltd	Japan		
JP3441600008	Taiko Bank Ltd	Japan		
JP3502200003	Daiwa Securities Group Inc	Japan		
JP3511800009	Chiba Bank	Japan	✓	
JP3520000005	Chukyo Bank Ltd	Japan		
JP3521000004	Chugoku Bank Ltd	Japan		
JP3587000005	Tokyo Tomin Bank Ltd	Japan		
JP3601000007	Toho Bank Ltd	Japan		
JP3630500001	Tomato Bank Ltd	Japan		
JP3653400006	Nanto Bank Ltd	Japan		
JP3762600009	Nomura Holdings	Japan	✓	
JP3769000005	Hachijuni Bank	Japan		
JP3783800000	Higo Bank	Japan		
JP3786600001	Hitachi Capital Corporation	Japan		
JP3833750007	Promise Co Ltd	Japan		
JP3841000007	Hokuetsu Bank Ltd	Japan		
JP3881200004	MIE Bank Ltd	Japan		
JP3888000001	Michinoku Bank Ltd	Japan		
JP3905850008	Minato Bank Ltd	Japan		
JP3932800000	Mizuho Trust & Banking Co Ltd	Japan		
JP3942000005	Yamanashi Chuo Bank Ltd	Japan		
JP3955400001	Bank of Yokohama	Japan	✓	
NO0006000801	Sparebank 1 Nord-Norge	Norway		
NO0006000900	Sparebanken Vest	Norway		
PTBCP0AM0007	Banco Comercial Portugues / Millennium bcp	Portugal		
PTBES0AM0007	Banco Espirito Santo Group	Portugal	✓	

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Table B.1 – continued from previous page

ISIN code	Bank Name	Country	Big	G-SIFI
PTBNF0AM0005	BANIF SGPS SA	Portugal		
PTBPI0AM0004	Banco BPI SA	Portugal		
SE0000148884	Skandinaviska Enskilda Banken Group	Sweden	✓	
SE0000193120	Svenska Handelsbanken	Sweden	✓	
SE0000242455	Swedbank	Sweden	✓	
SE0000427361	Nordea Group	Sweden	✓	✓
US0258161092	American Express Company	US	✓	
US0454871056	Associated Banc-Corp	US		
US0462651045	Astoria Financial Corporation	US		
US0549371070	BB&T Corp	US	✓	
US05561Q2012	BOK Financial Corporation	US		
US0596921033	Bancorpsouth Inc	US		
US0605051046	Bank of America	US	✓	✓
US0625401098	Bank of Hawaii Corporation	US		
US0640581007	Bank of New York Mellon	US	✓	✓
US14040H1059	Capital One Financial Corporation	US	✓	
US1491501045	Cathay General Bancorp Inc	US		
US1729674242	Citigroup	US	✓	
US1785661059	City National Corporation	US		
US2003401070	Comerica Incorporated	US		
US2005251036	Commerce Bancshares Inc	US		
US2298991090	Cullen/Frost Bankers Inc	US		
US2692464017	ETrade Financial Corporation	US		
US27579R1041	East West Bancorp Inc	US		
US3134003017	Freddie Mac	US		
US3135861090	Federal National Mortgage Association-Fannie Mae	US		
US3167731005	Fifth Third Bancorp	US	✓	
US31946M1036	First Citizens BancShares	US		
US3205171057	First Horizon National Corporation	US		
US33582V1089	First Niagara Financial Group Inc	US		
US3379151026	FirstMerit Corporation	US		
US3379305077	Flagstar Bancorp Inc	US		
US3546131018	Franklin Resources Inc	US		
US3602711000	Fulton Financial Corporation	US		
US38141G1040	Goldman Sachs	US	✓	✓
US4436831071	Hudson City Bancorp Inc	US		
US4461501045	Huntington Bancshares Inc	US		
US4508281080	Iberiabank Corporation	US		
US4590441030	International Bancshares Corporation	US		
US46625H1005	JPMorgan Chase & Co	US	✓	✓
US4723191023	Jefferies Group Inc	US		
US4932671088	KeyCorp	US		
US55261F1049	M&T Bank Corporation	US		
US55264U1088	MB Financial Inc	US		
US5718371033	Marshall & Ilsley Corporation	US		
US6174464486	Morgan Stanley	US	✓	✓
US6494451031	New York Community Bancorp Inc	US		
US6658591044	Northern Trust Corporation	US		
US6934751057	PNC Financial Services Group	US	✓	

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Table B.1 – continued from previous page

ISIN code	Bank Name	Country	Big	G-SIFI
US7127041058	People's United Financial Inc	US		
US7429621037	Privatebancorp Inc	US		
US7547301090	Raymond James Financial Inc	US		
US7591EP1005	Regions Financial Corp	US	✓	
US78442P1066	SLM Corporation-Sallie Mae	US		
US78486Q1013	SVB Financial Group	US		
US8085131055	Charles Schwab Corporation	US		
US8574771031	State Street Corp	US	✓	✓
US8679141031	SunTrust Banks	US	✓	
US8690991018	Susquehanna Bancshares Inc	US		
US87161C1053	Synovus Financial Corp	US		
US8722751026	TCF Financial Corporation	US		
US87236Y1082	TD Ameritrade Holding Corporation	US		
US9027881088	UMB Financial Corporation	US		
US9029733048	US Bancorp	US	✓	
US9042141039	Umpqua Holdings Corporation	US		
US9197941076	Valley National Bancorp	US		
US9388241096	Washington Federal Inc	US		
US9478901096	Webster Financial Corp	US		
US9497461015	Wells Fargo & Co	US	✓	✓
US97650W1080	Wintrust Financial Corporation	US		
US9897011071	Zions Bancorporation	US		