DYNAMIC FACTOR MODELS AND FINANCIAL CONNECTEDNESS: AN APPLICATION TO THE MAJOR NATIONAL BANKING SYSTEMS AROUND THE WORLD

by

Mert Demirer

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Abstract

This paper analyzes the volatility connectedness of major banking systems around the world. Incorporating dynamic factor models into Diebold-Yılmaz connectedness framework (Diebold and Yilmaz, 2011), we calculate volatility connectedness measures for national banking systems rather than individual banks. In each country, bank stock return volatilities are assumed to be driven by a common country factor and an idiosyncratic component unique to each bank. In the first stage, for each national banking system, we obtain the common country factor is calculated as the first principal component of the bank stock return volatilities. In the second stage, we construct a VAR model of the country volatility factors and undertake the variance decomposition analysis of volatility shocks to obtain the Diebold-Yılmaz connectedness measures. We obtain both static and dynamic measures of connectedness. In the static analysis we show that the volatility connectedness of countries are closely linked to major banking system characteristics. First, banking systems located in the same region of the world tend to be more connected with each other in volatility than with those outside the region. Second, national banking systems tend to generate net volatility connectedness towards others as their size and financial development levels rise. In the dynamic rolling window analysis, we obtain important results related to both systemic volatility and volatility transmitted by national banking systems. In terms of systemic risk, we manage to capture the main stages of the recent global financial crisis by our total connectedness index. We find that the US was the main generator of volatility to other countries from the onset of the US financial crisis until the end of 2008. However, once the crisis became global and was followed by the sovereign debt/banking crisis in the Eurozone periphery, the "to-connectedness" of the European banking system, and especially the ones in the southern periphery, increased substantially.

Keywords: Financial connectedness, dynamic factor models, risk measurement, systemic risk, systemically important financial institutions, vector autoregression, variance decomposition

Özet

Bu çalışma dünyadaki belli başlı bankacılık sistemleri arasındaki oynaklık bağlanmışlığını analiz etmektedir. Temel bileşenler analizini Diebold-Yılmaz bağlanmışlık metodolojisine eklemleyerek oynaklık bağlanmışlığını bankalar yerine ülkeler düzeyinde ölçmektedir. Analizdeki her ülke için, banka hisse senedi getiri oynalığının ortak bir ülke faktörü ve her bankaya özgü bir bileşen tarafından belirlendiği varsayılmaktadır. Ortak ülke faktörü o ülkede faaliyet gösteren bankaların günlük getiri oynaklığının ilk temel bileşeni elde edilerek hesaplanmaktadır. Elde edilen faktörlerle vektör otoregresyon modeli kurularak Diebold-Yılmaz modelinin varyans ayrıştırması analizi gerçekleştirilmiştir. çalışmada hem durağan hem de devingen bağlanmışlık analizi sunulmaktadır. Durağan analizde ülkelerin oynaklık bağlanmışlığının bankacılık sistemlerinin temel özellikleriyle yakından ilişkili olduğu gösterilmiştir. İlk olarak, aynı bölgede yer alan bankacılık sistemlerinin, birbirleriyle bölge dışındakilere göre daha bağlantılı olduğu ortaya çıkmıştır. İkinci olarak ise bankacılık sistemlerinin büyüklüğü ve finansal gelişmişliği arttıkça daha çok net oynaklık yaydıkları gösterilmiştir. Devingen analizde ise hem ülkelerin yaydığı oynaklık hem de global sistemdeki toplam riskle ilgili önemli bulgular elde edilmiştir. Analizde sunulan sistemik risk endeksi, son yaşanan finansal krizin önemli dönüm noktalarını yakalamaktadır. Krizin başlangıcından 2008 yılının sonuna kadar Amerika Birleşik Devletlerinin en önemli oynaklık kaynağı olduğu ortaya çıkmıştır. Ancak krizin global seviyeye ulaşıp, Avrupa ülkelerinin borç sorunlarınlarının etkisiyle Avrupa'ya sıçramasıyla birlikte Avrupa bankacılık sistemlerinin, özellikle çevre ülkelerinin etkisinin arttığı görülmektedir.

Anahtar Kelimeler: Finansal bağlanmışlık, dinamik faktör modeli, risk ölçümü, sistemik risk, sistemik öneme sahip finansal kuruluşlar, vektör otoregresyon, varyans ayrıştırması

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1 Introduction

As a result of the concerted efforts towards financial liberalization, financial markets around the world are more interconnected today than they had been thirty years ago. Capital can now freely flow across borders to seek out the best investment opportunities. While more integrated financial markets improve the resource allocation at a global scale, the risks stemmed from financial globalization cannot be ignored. The drawbacks of excessive capital flows have become apparent following the outburst of financial crises in emerging market economies in the 90s. Despite the lessons drawn from emerging market economies, until recently, developed financial markets were thought to be prone to excessive risks. The recent global financial crisis showed that poorly measured and, therefore, poorly managed risk can lead to catastrophic results not just for one market or country, but for the whole financial system.

In the aftermath of the global financial crisis, the literature on the measurement and management of risk has blossomed very quickly. In this brave new world, this literature received great attention in the academic and policy circles. To name a few, Acharya et al. (2010), Adrian and Brunnermeier (2011) and Diebold and Yilmaz (2011) proposed new frameworks towards the measurement of systemic risk using alternative approaches.

The aim of this paper is to contribute to this burgeoning literature on systemic risk measurement. In particular, we propose extending the Diebold-Yilmaz (henceforth DY) financial connectedness framework, such that it can be used to analyze datasets with a larger cross sectional dimension. The use of dynamic factor models in risk measurement, which allows us to achieve dimension reduction, lies at the heart of our contribution. This feature of the analysis differentiate our study from the literature in the sense that we are able to exploit a higher dimensional dataset in connectedness measurement. In our framework, we analyze volatility connectedness across 208 bank stocks operating in fourteen countries. For each country in the sample, we estimate a country volatility factor which is assumed to drive daily volatility of bank stock operating in that country. The factor is calculated as the first principal component of banks in that country. After this estimation, we include fourteen country volatility factors in the VAR model and obtain connectedness measures a la DY.

Our interest in incorporating dynamic factor model into DY connectedness methodology is motivated by complexity of connectedness. Today, countries are connected to each other through various links formed as a result of increasing globalization in recent decades. This nature of the connectedness calls for a comprehensive approach in which economists are able to exploit high dimensional datasets. Nevertheless, the majority of the econometric approaches in the risk measurement literature such as VAR in DY framework does not allow researchers to use more than a few dozen variables. In order to overcome this problem, we propose to include dynamic factor model in DY connectedness model. This strategy enables us to increase the number of bank stocks in the analysis from a few dozens to a few hundreds.

Another notable advantage of using dynamic factor model is that we are able to measure volatility connectedness at the country level rather than the institutional level as in DY. In the literature, source of the risk in financial markets is considered the vulnerability of the individual financial firms. Even though institution-dependent vulnerabilities are significant risk generating factors, we believe that country-specific factors cannot be ignored. Banks operating in the same country are exposed to the same regulation and the same fiscal and monetary policies. Besides, macroeconomic performance of a country has also considerable influence on the risk assessment of financial institutions. For example, during the recent financial crisis, it turns out that the problem is not due to the risks taken by a few financial institutions. Indeed, most of the US banks suffered from similar problems as a result of lack of regulation and policies adopted before the financial crisis. Motivated by these observations, we focus on country level connectedness by excluding institutional specific factors.

The remainder of the study is organized as follows. The next section covers the relevant studies in risk measurement literature focusing on those developed after the recent financial crisis and introduces dynamic factor models with the aim of explaining its role in the economics literature. Section three describes the dataset. In section four the methodology is explained. Section five presents estimated country volatility factors. In section six, results of DY analysis are indicated. The final section concludes the paper.

2 Literature Review

2.1 Systemic Risk Measurement

Systemic risk is a very broad and abstract term. It is difficult to represent it in a number. Therefore, there is no consensus in the academic and policy circles on the definition and the measurement of the systemic risk. For this reason, the methods used by studies aimed at measuring systemic risk vary a lot.[1] The most known and direct way to measure the systemic risk is the probability distribution models. This measurement technique is based on the joint distribution of negative outcomes of a set of important financial institutions. The prominent examples of this method are CoVAR approach of Adrian and Brunnermeier (2011) and the framework developed by Acharya et al. (2010) both of which focus on co-dependence in the tails of equity returns of financial institutions. Adrian and Brunnermeier (2011) proposes a framework which calculates each financial institution's contribution to the systemic risk. They exploit Value at Risk (VaR) methodology by calculating it conditional on different state of financial institutions (CoVAR). Following this step, an institution's contribution to the systemic risk is defined as the difference between CoVAR conditional on the institution being in distress and CoVAR conditional on in the middle of the distribution. Second approach is developed by Acharya et al. (2010). They propose a measurement technique, systemic expected shortfall (SES), defined as the contribution of an institution to the systemic risk. The SES measurement is based on the performance of financial institutions in distressed times. They use three different criterion to measure the performance of financial institutions: stress test performance, equity valuation and CDS spreads. After defining and calculating SES, they seek to develop two leading indicators, marginal expected shortfall (MES) and leverage (LVG) which predict the institution's SES. Another study that focuses on the tail risk is Brownlees and Engle (2012) which defines the systemic risk of a financial institution as its contribution to the total capital shortfall of the financial system that can be expected in a

[1] For a survey see Bisias et al. (2012) and Hansen (2012)

future crisis.

Contingent claim analysis is another approach used in systemic risk measurement. Gray and Jobst (2011) propose a methodology that measures systemic risk from market-implied expected loss. Based on option pricing theory, they also quantify the individual contribution of financial institutions to total contingent liabilities in the case of a systemic distress.

The use of principal component estimation in the risk measurement literature is also available. There are two studies that carry out principal component estimation in systemic risk measurement. Even though, the role of the principal component analysis in these studies is different from our goal, they are worth to be briefly mentioned. Kritzman and Li (2010) propose to measure system risk via Absorption Ratio (AR) which is defined as the total variance of a set of asset explained by a smaller set of factors. According to Absorption Ratio calculated through principal component analysis, they classify financial markets as unified or tightly coupled. The rationale behind the measurement is that when absorption ratio is high, the degree of comovement of assets is also high, implying that a shock to the system propagates very quickly and broadly. In the opposite case where the ratio is low, assets in the market are less connected to each other, hence, a shock to an asset goes away without affecting other assets to a large degree. Second paper that employs principal component analysis is Billio et al. (2010). This study seeks to capture connectedness among the monthly returns of hedge funds, banks, brokers and insurance companies. The idea of this study is similar to the previous study in the sense that what it does is to obtain first principal component of the four variables in order to see the degree of comovement between them. When the variance explained by the first principal component is large enough for all institutions in the sample, they conclude that the systemic risk in the financial markets is also high.

2.2 Dynamic Factor Models

Although factor models have been widely used in psychology since the beginning of the 20th century, its application to economics started with Geweke (1977) and Sargent and Sims (1977). They introduced the dynamic factor model by adding time dimension to static factor analysis which is the one applied in social sciences. Their frameworks simply use frequency domain to look for an evidence whether time series can be represented by a few factors. In addition to this, how successful the factors are in explaining macroeconomic variables is also of interest in the early literature.

Starting in early 1990's, with the increase in the number of series available to be used for economic studies, factor models became a popular tool in economics. Furthermore, the improvements in computational technology helped researchers develop more comprehensive factor estimation models. For these reasons, the interest switched from frequency domain approach to time domain approach which is more appropriate for proper estimation of the factors. Since then, several methods have been developed to estimate factors for a variety of purposes.

We can categorize the time domain factor estimation models in four generations. The first generation is based on Gaussian maximum likelihood estimation of the state space representation of factor models. This method obtains the parameter estimation of the model through Kalman Filter under the appropriate model assumptions. However, since the number of parameter to be estimated in the linear optimization model is in general very large, non-linear optimization methods, which bring computational constraints, have been used. Therefore, for very large datasets, this method is computationally infeasible. Quah and Sargent (1993) who used expectation-maximization algorithm for maximum likelihood estimation of factors for 60 series is one of the largest example of the first generation. Kalman Filter algorithm in factor estimation have been used by several purposes such as forecasting (see Stock and Watson (1989)) and real time indexing with missing data (see Aruoba et al. (2009)).

The second generation factor estimation applies non-parametric estimation methods with large sample (N) using cross-sectional averaging methods. Among them, principal components method and its variations have been widely used especially for forecasting. The main advantage of the principal components is its easy implementation for very large dimensional datasets. Different versions of the principal component estimation of factor models have been studied for many years. For example Stock and Watson (2002) showed the consistency of principal component estimator of factors as number of series and observation goes to infinity. Another approach which solves principle components estimation by weighting matrix is generalized principal component estimation method. Forni et al. (2005), Boivin and Ng (2005) and Stock and Watson (2005) offered three different applications of this approach. The last variation of the principal components method is dynamic principal components which is the frequency domain implication of generalized principal component methods Forni et al. (2000). However, this approach cannot be directly applied to factor estimation in the time domain.

The third generation of the factor models use a combination of the first and the second generation models. It mainly consists of two steps. First, factors and parameters are estimated with principal components. In the second step, estimated factors and parameters are used in Kalman Filter algorithm as initial values to decrease number of parameters to be estimated. This method makes use of applicability of Kalman filter to dataset with mixed frequency and unlimited dimension of principal component estimations methods.

The last approach to the estimation of factor models relies primarily on Bayesian methods. This approach has several advantages. First, like the principal components method, it has no dimensionality problem thanks to Markov Chain Monte Carlo methods that can be applied in different ways. Second, calculating posterior is easier and more stable than the likelihood function of Kalman Filter method. Lastly, if any initial information or beliefs available, it can be included in the model using prior distributions. Otrok and Whiteman (1998) use Bayesian methods to develop a business condition index for Iowa. More recently, Ayhan Kose et al.

(2008) estimated global, regional and country-specific factors for 60 countries to examine synchronization of business cycle of developed and developing countries. B. Bernanke and Boivin (2003) introduced a novel factor-augmented vector autoregression (FAVAR) framework that estimated and used factor extracted from more than 200 variables and used the factors in VAR analysis along with three real observed variables.

3 Data

In this study, to estimate the banking volatility factors at the country level we use return volatility of banks stocks. Following the factor estimation, estimated country volatility factors are treated as given data to analyze connectedness. Since volatility is latent, we use range volatility which is estimated using the highest and the lowest prices of the stock within a given day. Therefore, the dataset involves daily stock market data of the interested banks.

Our dataset covers the period from July 2003 to January 2013. We have 207 banks in our sample from fourteen countries. The chosen period reflects the intention to cover the recent financial crisis and preceding boom in stock markets. In addition, the choice of 2003-2013 period reflects the desire to include as many banks as possible in the analysis. In that sense, there is a trade-off between these two issues. The reason for this trade-off is that initial public offering date of some important banks coincides with the period we intend to cover. Since we mostly include developed countries' banking systems, only China has relatively important banks whose initial public offering took place in the second half of the last decade. Given that China is becoming a global actor and its influence in the global economy is gaining attention, we opt for including China in our sample. However, in order to see the effects of the two biggest excluded banks, we compare the original factor with the one obtained by adding excluded banks for the last five years. Strong correlation between two factors leads us to conclude that two banks that are not included in the dataset do not have a significant effect on Chinese volatility factor.

Factor estimation requires that the variables of the model are stationary. For that reason, we use logarithms of the estimated range volatility of bank stocks in our factor model estimation. This estimation is also appropriate for the generalized variance decomposition analysis carried out in the DY framework because the volatility itself is not approximately normal. Finally, in order to make all series internally consistent, we standardize them before principal component estimation so that they have zero mean and one standard deviation.

4 Methodology

The main contribution of this paper is to incorporate dynamic factor models into DY connectedness framework to make use of larger dimensional datasets. Therefore, the methodology of this paper consists of dynamic factor model estimation and connectedness estimation of DY methodology. More specifically, we follow two separate steps. First, the dynamic factor model estimation is carried out and country banking volatility factors are obtained. Following this step, we use the estimated factors to undertake DY analysis. As our study involves two distinct steps, this section examines dynamic factor model and DY methodology separately.

4.1 Factor Estimation

Dynamic factor model is build upon the assumption that a set of variable with strong co-movement is driven by a smaller number of unobserved factors and idiosyncratic component of each variable. In our setup, we assume that there exists an unobserved volatility factor for each country that drives volatility of bank stock returns of financial institutions originated in that country. This assumption allows us to reduce the dimension from the number of banks in that country to one. Therefore, the number of country factors in the VAR analysis is equal to number of countries. The formal model is as follows.

Let $X_t = (x_{1,t}, x_{2,t}, ..., x_{n,t})$ $1 \times n$ matrix denotes the daily stock volatility of n financial firms in the sample. We assume that X_t evolves according to following equations

$$X_t = \wedge F_t + \varepsilon_t \tag{1}$$

$$F_t = A(L)F_{t-1} + \eta_t \tag{2}$$

where F_t is $k \times 1$ unobserved time series factor which represent common dynamics of banks operating in the same country, $\wedge$ is $1 \times n$ factor loading matrix, ε_t is a vector of idiosyncratic components that are assumed to have zero mean and serially and cross sectionally uncorrelated, $\eta_t is\ k \times 1$ idiosyncratic components of VAR process and A(L) is polynomial matrices. The idiosyncratic disturbances are assumed to be uncorrelated with the factor innovations at all leads and lags, that is, $E\varepsilon_t\eta_{t-k} = 0$ for all k.

We have an additional restriction on the matrix of factor loading such that the only factor that affects the volatility of banks stock return is the factor for the country in which the bank operates. That is, the parameters of the loading matrix attached to different country factors are zero. Therefore, we can split the first equation and write it in a different form such that

$$X_{i,t} = \wedge_i F_{i,t} + \varepsilon_{i,t} \tag{3}$$

where $F_{i,t}$ is 1×1 unobserved time series factor which is defined as volatility factor of i_{th} country, $\wedge_i$ is $1 \times n$ loading matrix and ε_t is a vector of idiosyncratic components that are assumed to have zero mean and serially and cross sectionally uncorrelated.

To estimate parameters in the model, we follow two steps. First, the parameters of the first equation and country factors are estimated by extracting the first principal component of daily stock return volatility of banks operating in the same country. In the second step, we use estimated factors in the first step to run VAR equation to estimate remaining parameters in the second equation. As discussed in the dynamic factor model section, there are several methods that estimate parameters simultaneously. However, for studies that includes large dataset, it is computationally infeasible to apply most of the estimation methods. Since our dataset covers more than two hundred variables, the number of parameters that is needed to be estimated exceeds five hundred depending on the number of lags in the VAR equation. Therefore, most of the classic estimation methods such as the Kalman filter or the maximum likelihood estimation cannot be applied to our model. In fact, this problem became very common in recent years as economists tend to use very large dimensional datasets. The improvement in information technology enabled economists to use enormous number of variables. For that reason, there is na increasing tendency to use of principal component methods in factor estimation literature.

However, infeasibility of the other methods is not the only reason why we apply principal component estimation. There are many studies in the literature that provides evidence in favour of principal component estimation. First, Stock and Watson (2002) show that if cross section (N) and time (T) dimension are large enough, principal component estimation gives consistent estimators of the factor asymptotically. Although N and T must converge to infinity to satisfy asymptotic theory, studies by Inklaar et al. (2003) and Boivin and Ng (2006) raise some doubts about the importance of having a large cross sectional dimension [2]. By conducting Monte Carlo simulation Boivin and Ng (2006) demonstrate that increase in cross sectional dimension does not necessarily improve factor performance. Parallel to this observation, a literature performing principal component estimation with a small cross sectional dimension emerged recently [3]. In our study, because number of bank varies among countries, the consistency performance of the country factors are different. However, for some countries with large number of banks we have sufficient number of banks to meet consistency. Second, some studies carry out both principal component and Bayesian estimation analysis and compare the results. Among them, Bernanke et al. (2005) states that the performance of Bayesian and principal components estimation are very similar. They add that the computational cost of Bayesian methods outweighs the gain obtained by Bayesian estimation. Secondly, Helbling et al. (2011) employs both Bayesian approach and principal components estimation for a analysis similar to ours and they conclude that both factors are almost identical.

[2] For a discussion see Heaton and Solo (2006)

[3] see Kose et al. (2012), Bagliano and Morana (2010) and Lombardi et al. (2012)

Since both the factor and the loadings are unknown, the above equation cannot be uniquely estimated without additional identification. Suppose $\wedge_i$ and F_i are true the loading and the factor. By picking an invertible $n \times n$ matrix Q, we obtain the same equation with the new factor of QF_i and new loading matrix of $\wedge_i Q^{-1}$ whose multiplication gives the same matrix. $\wedge_i Q^{-1} QF_i = \wedge_i F_i$. Therefore we put an additional restriction, $F^{-1}F = I$ to uniquely identify the factor and the loading matrix. In fact, principal components gives a space that can be spanned by infinitely many vectors. By this restriction, we identify the unique factor which spans the space obtained by the first principal component. Since what we are interested are not the factors itself, identification strategy does not restrict us in the further steps.

In this first step, we estimate the parameters of constructed factor models. The parameters obtained in this step is treated as given parameters in the estimation procedures of DY in the second step.

4.2 DY Connectedness Methodology

DY connectedness measurement is based on the variance composition associated with N variable vector autoregression. Consider a covariance stationary N-variable VAR(p), $x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$, where $\varepsilon_t \sim (0, \Sigma)$. The moving average representation is $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where the NxN, coefficient matrices A_i p order autoregressive process $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$, with A_0 an NxN identity matrix and $A_i = 0$ for $i < 0$. MA representation of VAR is used to estimate the effects of shocks to variable x_i to the forecast of variable x_j for $i, j = 1, 2, .., N$. From this representation own variance shares is defined as the fraction of H-step-ahead error variances in forecasting x_i due to x_i and connectedness is defined as fraction of H-step-ahead error variances in forecasting x_i due to shocks x_j for all i, j.

This representation of connectedness requires the derivation of the impulse response function of VAR(p) process which is obtained a la Pesaran and Shin (1998).

They show that when the error term ε_t has a multivariate normal distribution, the H-step generalized impulse response function scaled by the variance of the variable is given by:

$$\gamma_j^g(h) = \frac{1}{\sqrt{\sigma_{jj}}} A_h \Sigma e_j, \qquad h = 0, 1, 2, ... \tag{4}$$

where Σ is the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the j^{th} equation and e_i is the selection vector with one as the i^{th} element and zeros otherwise.

The last step to obtain the connectedness index is to calculate each variable's contribution to each other's H-step-ahead generalized forecast error variance. This is calculated by the following formula

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \tag{5}$$

Since the sum of each row of the variance decomposition matrix is not necessarily equal to one, we normalize each entry of the decomposition matrix to obtain index from variance decomposition. This is performed by dividing each entry by row sum,

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^{N} \theta_{ij}^g(H)} \tag{6}$$

Finally using the normalized entries of the variance decomposition matrices DY define four different connectedness measures: the total connectedness $C(H)$, the gross directional connectedness received by variable i from all other variables j $C_{i \leftarrow \bullet}$ (from connectedness), the gross directional volatility connectedness transmitted by variables i to all other variables j $C_{\bullet \leftarrow i}$ (to connectedness), and finally, the net directional connectedness transmitted from variable i to all other variables $C_i(H)$ (net connectedness),

$$C(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}^{g}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^{g}_{ij}(H)} = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}^{g}_{ij}(H)}{N} \tag{7}$$

$$C_{i \leftarrow \bullet} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}^{g}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^{g}_{ij}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}^{g}_{ij}(H)}{N} \times 100 \tag{8}$$

$$C_{\bullet \leftarrow i} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}^{g}_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^{g}_{ji}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}^{g}_{ji}(H)}{N} \times 100 \tag{9}$$

$$C_i(H) = C_{\bullet \leftarrow i}(H) - C_{i \leftarrow \bullet}(H) \tag{10}$$

5 Estimates of Country Factors

This section presents the results of the first stage of the empirical analysis. We examine the evolution of country volatility factors estimated as common volatility movement of stocks of banks operating in each country. Since country volatility factors estimated independently, this section gives important country-specific insights on the evolution of volatility in each banking system in our sample.

We estimate fourteen country factors using principal component analysis assuming that a country factor is the only variable that drives volatility of bank stock returns in a single country. Due to the assumption that we have only one factor in each country, the first principal component is taken as the country factor. Figure 1 shows the evaluation of factors from July 2003 through January 2013. Since we standardize the data before the estimation of the factors, value of the factors fluctuate around zero. Compared to range volatility data calculated for each bank in the sample, country volatility factors are smoother and they fluctuate in a narrower range. This behaviour stems from the fact that dynamic factor models calculates common movements of bank stock returns volatility excluding their idiosyncratic components which tends to be more volatile.

The recent global financial crisis plays an important role in explaining volatility characteristics of the banking systems. That is one of the reason why we observe strong similarities among country factors. For example, before the financial crisis, a majority of the factors was below zero line. However, as soon as the financial crisis erupted in 2007, they jumped to the positive region of the graph, peaked in 2008 and remained there until recently. The exceptions are Asian countries in the sample, Japan, Korea and China, whose factors are less volatile compared to other countries. Moreover, except for the period when the crisis peaks, volatility factors of these countries fluctuate around zero. Hence, they do not exhibit different pattern before and after the crisis. Based on this observation, we can claim that Asian countries decoupled from Western countries in terms of volatility during the crisis. Examining country factors individually also offers us some useful insights

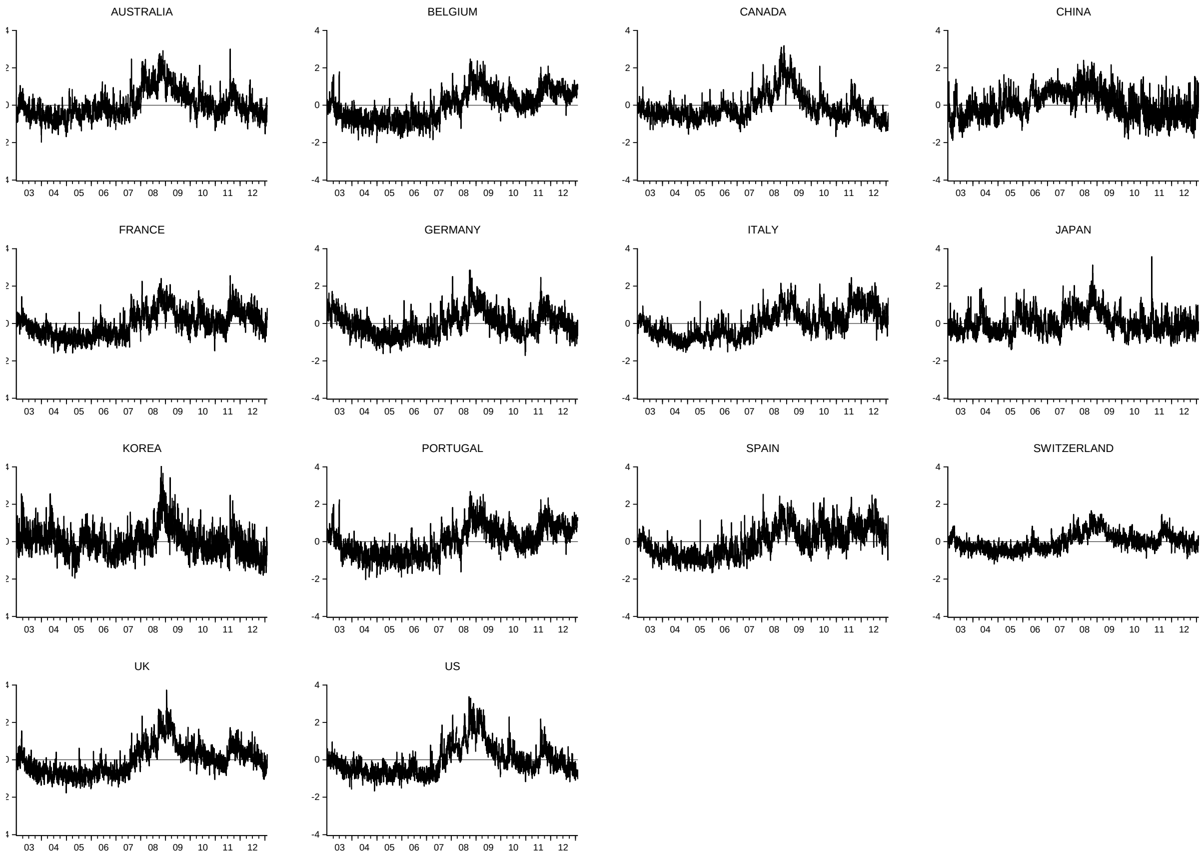

Figure 1: Estimated Country Factors

about the influence of the financial crisis on different countries. During the period that preceded the crisis, the volatility factor of the US, the origin of the financial crisis, increased significantly. During the same period, countries, for instance UK and Canada, that seem to be strongly connected to the US also had high volatility factors along with the US. However, at the onset of the crisis, volatility factors of the European countries have not increased that significantly. As the crisis became global with Lehman Brother bankruptcy, almost all countries' volatility factors reached their peaks. After the peak, volatility factors started to fall again reflecting the expectation in the financial markets that the worst was behind. However, another jump is observed in the volatility factors during 2011 in which concerns on European sovereign debt crisis has risen. During this period, volatility factors of almost all European countries jumped to a level as high as that of 2008. For most of the European countries, the volatility factors moved down as worries on debt crisis subsided down. Volatility factors of those who are the at the epicentre of the debt crisis remained high for a prolonged time period until the European Central Bank's pledge that they would do whatever it takes to save the Euro.

The question of how much variation in the original series is explained by the factors is as important as the factors itself. To evaluate the performance of the factors, we report the percentage of variance of original series explained by the factors in a separate column on the bank tables presented in the appendix. In addition, Figure 2 shows the relation between market capitalization of the banks and variance explained by the country volatility factor. There are two main elements that affect the performance of the factor. The first and the technical one is the number of banks available in a country banking system. Since the principal component estimation captures the co-movements of banks' stock return volatility, as the number of banks rises, the degree of co-movements in the system declines. Another important determinant of the performance of the factor is country-specific features of the banking systems. Small and regional banks tend to have larger idiosyncratic components and hence lower share of variance explained by the country factor. Therefore, in countries based on more regional and small banks, performance of

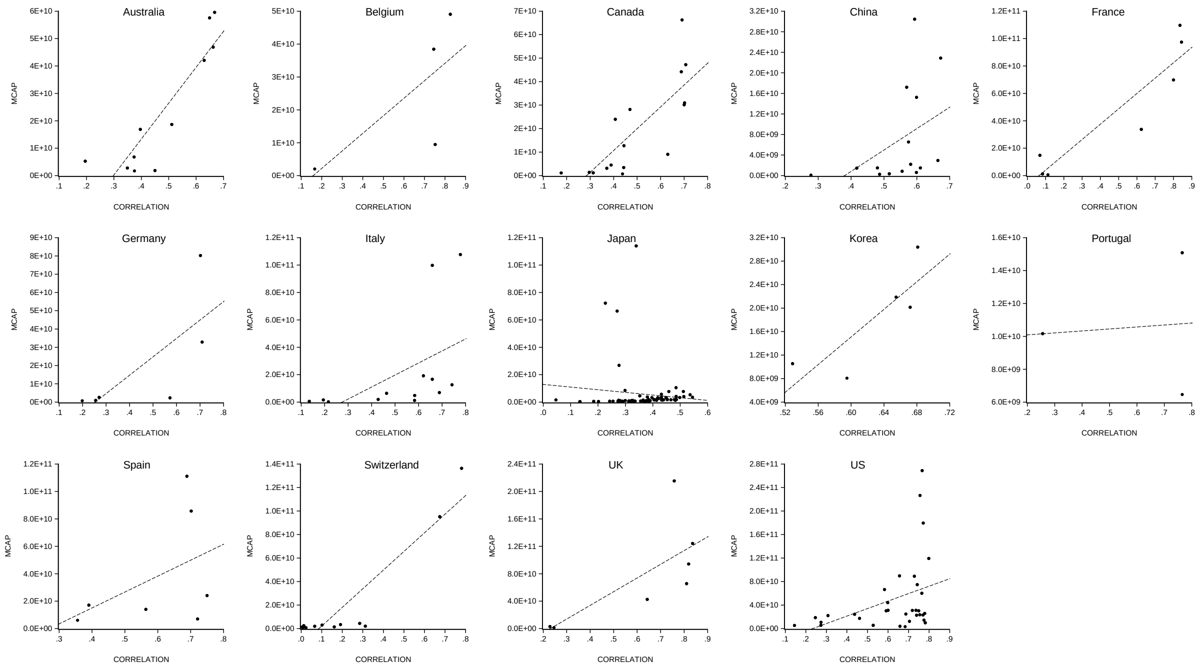

Figure 2: Correlation Between Country Factors and Volatility of Bank Stock Returns

the factor is likely to be worse. For instance, despite the high number of banks in the US, the country factor explains more than fifty percent of variations of volatility of most of the banks. However, for Japan, another country with a high number of banks, there are no banks whose fraction stock return volatility explained by the factor exceed 60 percent. Moreover, there are only a few banks with more than fifty percent variation explained by Japan's volatility factor. This comparison underlines the fact that banking tradition of a country plays an important role in the degree of volatility correlation between banks.

In our sample, we differentiate between banks in terms of their market capitalization values. In terms of market capitalization, our bank sample varies significantly, covering the biggest systemically important global banks as well as small, regional banks. Based on this highly wide and differentiated sample, one might argue that small banks has no importance in volatility spillover compared to large, systemically important banks. It can even be argued that the behaviour of small banks is driven by their own idiosyncratic components only. In order to analyze the effects of the market capitalization on the portion of the variance explained by factors, we plot the two variables in Figure 2. Clearly, with the exception of the Japanese banking system, the share of the variance explained by the factor rises as market capitalization increases for all banking systems. This observation reflects the fact that correlation between large banks is higher and, therefore, they play more important role in generating volatility. Our factor model capture this phenomenon by putting more weight to banks with higher market capitalization. Therefore, in averaging volatility of bank stock returns, we rely on more consistent weighting mechanism rather than simply averaging all banks in the sample.

6 DY Connectedness Analysis

This section takes the first step towards connectedness analysis by displaying full sample connectedness result. The goal of this section is to obtain the position of the countries in the transmission of volatility around the world. Lastly, with the aim of capturing dynamic feature of volatility connectedness, we interpret the result of total volatility index and directional volatility of countries in the light of developments in the financial markets occurred in the corresponding time period.

6.1 Static Analysis

As stated in the introduction, our aim is to capture how connectedness between national banking systems evolves over time in response to the developments in the global financial markets. However, before moving to the dynamic analysis of the volatility connectedness, we perform static analysis of connectedness using the full sample dataset in order to characterize the links between countries. Table 1 presents the results of the full sample analysis. In the full sample analysis, the interest is to uncover volatility spillovers across countries by identifying how much a volatility shock to a country affects another country. In Table 1, we report a 14 by 14 matrix with three additional rows for “to”, “from” and “net” connectedness.

The entries in the table show how much volatility is transmitted from the country in the column heading to the country in the row heading. For example, the entry in the fifth row and third column gives the volatility transmitted from Canada to France as a result of a volatility shock to the Canadian financial system. Last three rows provide some summary results for each country by aggregating necessary pairwise connectedness values. “From” connectedness gives the sum of volatility shocks received from other countries, “to” connectedness sums up the volatility transmitted to other countries and “net” connectedness is the difference between “to” and “from” connectedness. In the rest of the section, we interpret full sample connectedness table focusing on regional links.

Asian countries’ “to” and “from” connectedness are significantly low compared to other banking systems in the sample. Except for Australia, they have the lowest “net” connectedness measures in absolute value. These two observations point out two important facts about Asian countries. On the one hand, negative “net” connectedness implies that Asian countries are net receiver of volatility shock, that is, they receive more volatility shocks than they give. On the other hand, in addition to their low profile in the global financial system, their links to the global financial system are not so strong given both low “to” and “from” connectedness. Among countries in Asia, China displays relatively distinct characteristics in terms of “to” and “from” connectedness. Its “to” connectedness of 6 and from connectedness of 12 are substantially lower than those of Japan and Korea, other Asian countries in the sample. These numbers show that the behaviour of Chinese banking system’s volatility is mostly driven by its own dynamics and China is not the source of volatility in the global financial system. The reason behind this fact is the closed capital account of China which restricts the movement of free capital. This observation also supports the view that capital flows play a crucial role in generating connectedness across countries. One may also expect that with its sophisticated financial market and developed economy, the role of Japan in volatility spillover should be high compared to other Asian countries. However, since 1990, Japan has suffered from two lost decades with deflation and poor growth performance.

	Australia	Belgium	Canada	China	France	Germany	Italy	Japan	Korea	Portugal	Spain	Switzerland	UK	US
Australia	39.03	2.74	9.57	2.13	4.05	3.17	2.75	2.39	0.43	2.11	3.31	6.03	7.60	14.67
Belgium	0.42	28.79	2.23	0.11	9.43	5.98	11.34	0.10	0.03	8.48	9.27	6.30	10.71	6.80
Canada	4.46	2.50	36.85	1.53	4.07	4.79	2.76	1.83	2.25	1.21	2.55	5.14	8.95	21.13
China	1.90	0.42	2.59	87.80	0.11	0.17	0.54	2.01	0.30	0.28	0.26	0.19	0.20	3.22
France	1.39	8.60	2.96	0.00	21.78	9.45	11.45	0.35	0.15	6.58	10.88	7.60	11.67	7.14
Germany	1.18	6.18	3.32	0.13	11.15	30.23	9.14	0.56	1.11	4.28	7.57	7.41	10.29	7.46
Italy	0.69	10.22	1.41	0.04	10.00	6.65	29.24	0.21	0.04	8.84	12.04	6.39	9.58	4.65
Japan	3.91	0.63	6.05	2.06	1.31	1.23	0.45	71.77	3.35	0.63	0.81	0.91	0.54	6.36
Korea	1.24	0.45	7.71	0.12	1.62	5.61	0.84	2.38	66.12	0.34	0.59	2.40	2.47	8.11
Portugal	0.39	9.27	0.58	0.03	7.49	4.31	11.99	0.08	0.08	37.34	10.40	5.09	7.22	5.73
Spain	0.60	9.49	1.12	0.02	10.76	6.16	14.14	0.18	0.06	8.57	27.46	6.03	10.23	5.18
Switzerland	2.47	6.15	4.88	0.09	8.40	8.08	8.49	0.96	0.43	5.20	7.76	25.43	11.26	10.41
UK	1.96	8.24	4.91	0.03	9.40	6.72	8.40	0.37	0.17	5.03	8.37	8.23	26.68	11.50
US	3.15	4.96	12.68	0.37	5.51	5.37	4.51	1.16	1.19	3.19	5.18	6.87	11.86	34.00
To	23.74	69.86	60.01	6.65	83.31	67.69	86.78	12.56	9.60	54.75	78.98	68.59	102.57	112.38
From	60.97	71.21	63.15	12.20	78.22	69.77	70.76	28.23	33.88	62.66	72.54	74.57	73.32	66.00
Net	-37.22	-1.35	-3.14	-5.55	5.09	-2.07	16.02	-15.67	-24.28	-7.91	6.44	-5.99	29.25	46.38

Table 1: Full-Sample Connectedness Table

. The sample is Dec 2, 2003 through February 5, 2013. The *ij*-th entry of the upper-left 14x14 country submatrix gives the *ij*-th pairwise directional connectedness; i.e., the percent of *12*-day-ahead forecast error variance of firms located in country i due to shocks from firms located in country j. The rightmost ("FROM") column gives total directional connectedness (from); i.e., row sums ("from all others to country i"). The bottom ("TO") row gives total directional connectedness (to); i.e., column sums ("to all others from country j"). The bottom-most ("NET") row gives the difference in total directional connectedness (to-from).

In that sense, Japanese economy decoupled significantly from the world economy both before and during the crisis. This fact can be highlighted with the second largest own connectedness number of 71.8% .

Another interesting observation is related to the Australian banking system whose "net" connectedness is the lowest in our country sample, reflecting the fact that its banking system volatility is driven primarily by the global forces rather than its own dynamics. However, when the "to" and "from" connectedness measures are examined separately, it is easily identified that the reason is very low "to" connectedness rather than high "from" connectedness. This observation points out that Australia's banking system volatility contribution to the global financial system is markedly less than what it receives from other countries. We can attribute this result to the isolated characteristic of the Australian economy. In the last decade, either before the crisis or during the crisis, Australia has never been the source of volatility in the global financial system.

The continental European banking systems exhibit similar behaviour in terms of "net" and "to" connectedness. Their "to" connectedness varies from 54% to 86% whereas the "net" connectedness ranges from -8% to 16%. We can divide European countries into two subgroups based on their role in volatility shock transmission originated in Europe. The first group is formed by France, Italy and Spain whose "to" connectedness are the highest among European countries with 83%, 86% and 79% respectively. Their total "net" connectedness are the only positive ones in Europe with 6%, 16% and 7% respectively. These numbers, and, therefore, their relative influence in volatility shock transmission is due to the fact that France, Italy and Spain are among the largest economies in Europe. The rest of the continental European countries, Belgium, Germany, Portugal and Switzerland are in the second group. The "net" connectedness of countries in the second group are all negative but not lower than -8%. This point underlines the fact that the distinction between two groups is not so deep. The only surprising result is the weak role of Germany, the biggest economy of the region. Germany's "from" and "to" connectedness are the second lowest after Portugal and its "net" connectedness is also negative. There may be two reasons that explain why the biggest economy of Europe is not so influential in terms of volatility connectedness. First, in the period we cover, Germany has not suffered from serious problems that could be the source of volatility to be spread to the other countries. On the contrary, the German economy has remained resilient during the crisis. Second, Germany has a unique banking system which relies on one gigantic bank, Deutsche Bank, which, at the same time, has stakes of various companies in non-financial sectors. This unique banking system may be the reason of volatility movement driven by its own dynamics.

In Europe, the UK has both the largest "to" and "net" volatility connectedness. After the US, it is also the second largest global volatility shock source in our sample. Therefore, the UK has significant contribution to volatility of other national banking systems. Thanks to its historical heritage, London is the main financial center through which a majority of the international financial transactions are conducted. Hence, it is more likely that a volatility shock to the UK banking system spreads to the other banking systems. Moreover, its positive "net" connectedness of 30,6% indicates that the UK gives more volatility shock than it receives in line with its special role in the global financial system.

From the other side of the Atlantic, we include two countries, Canada and the United States. Canada's "to" and "from" connectedness is slightly lower than that of the European countries but quite higher than that of Asian countries. This point suggests that the Canadian banking system is more closely connected with the global financial system compared to the Asian countries. On the other hand, the US is the dominant country in our sample in terms of the volatility shock transmission. With a "to" connectedness of 112% and a "net" connectedness of 47%, it is the main source of volatility shock along with the UK. However, as the biggest economy of the world, the influence of the US is higher than that of the UK.

So far, we analyze the role of countries in the global financial system in terms of

		Belgium	France	Germany	Italy	Portugal	Spain	Switzerland	UK
To	Europe	58.14	66.63	47.36	74.94	46.99	66.29	47.05	70.95
	Non-Europe	11.72	16.68	20.34	11.84	7.76	12.69	21.53	31.62
From	Europe	61.53	66.22	56.01	63.72	55.78	65.38	55.33	54.39
	Non-Europe	9.68	12.00	13.75	7.04	6.88	7.16	19.24	18.93
Net	Europe	-3.38	0.41	-8.66	11.22	-8.79	0.91	-8.27	16.57
	Non-Europe	2.03	4.68	6.58	4.81	0.88	5.53	2.29	12.69

Table 2: European Countries Connectedness

volatility connectedness without investigating their pairwise connectedness. However, static full sample analysis also gives important insights on the interaction of different banking systems. In order to capture the regional volatility connectedness, we analyze the banking systems by categorizing them based on the region they are located. To see the regional links across the European countries Table 2 presents "to", "from" and "net" volatility connectedness of the European countries classified under those associated with European countries and those associated with non-European countries. The most apparent regional links are among the European countries. Even though there are some differences in magnitude, for all European countries in the sample, volatility shock transmitted to the other European countries is much bigger than the volatility shock transmitted to the countries outside Europe. This difference is more obvious for "from" connectedness. All countries have positive "net' connectedness, meaning that Europe, as a whole, gives more volatility shock to outside of the continent than it receives. Within Europe, the UK and Italy provides the largest volatility spillover. However, all European countries have positive net connectedness with non-European countries ranging from 12.69 for the UK to 0.88 for Portugal. Thus, we can claim that Europe contributes more significantly to the generation of systemic risk. The distribution of "net" connectedness also provides important information on volatility connectedness within Europe. Both types of "net" connectedness supports the view that countries with larger GDP tend to give more volatility compared to those with lower GDP.

Another strong regional ties can be found between Canada and the US. For both countries, both pairwise "to" and "from" connectedness with each other are the largest. However, the share of volatility shock transmitted to Canada from the US, 21.13%, is higher than the volatility shock transmitted to the US from Canada, 12.68%. This observation reflects the influence of the US banking system on the Canadian financial system. The similar pattern is also evident for East Asian countries. However, as own connectedness is the key determinant of volatility movement of East Asian countries, the links are weaker as shown by low pairwise connectedness.

In addition to regional links discussed above, a detailed examination of the full sample table provides us with another way to group countries. Similar to banking systems in Europe, national banking systems outside the Europe also exhibit strong pairwise connectedness with each other. For example, “to” and “from” pairwise connectedness of the Australian and the Canadian banking systems is the largest for Australia and the second largest for Canada. Besides, almost all Asian countries are more linked to Canada and Australia than countries in Europe in terms of volatility connectedness. Given these strong ties within European and within non-European countries, we can claim that there is a decoupling in the global banking system.

6.2 Dynamic Analysis

The static analysis provides important insights on pairwise connectedness and countries' contribution to global volatility shocks. However, static analysis does not allow us to characterize the dynamics of the volatility connectedness. Given that the world economy has gone through the worst global financial crisis since the great depression, a study without dynamic aspect of the connectedness remains incomplete. Therefore, in order to capture the dynamics of connectedness over the last decade, we undertake a dynamic analysis using rolling estimation window. Rolling window analysis helps us understand the evolution of recent financial crisis through a set of indices. First, we focus on total connectedness index with the aim of identifying total systemic risk in the global financial markets. Following this, we

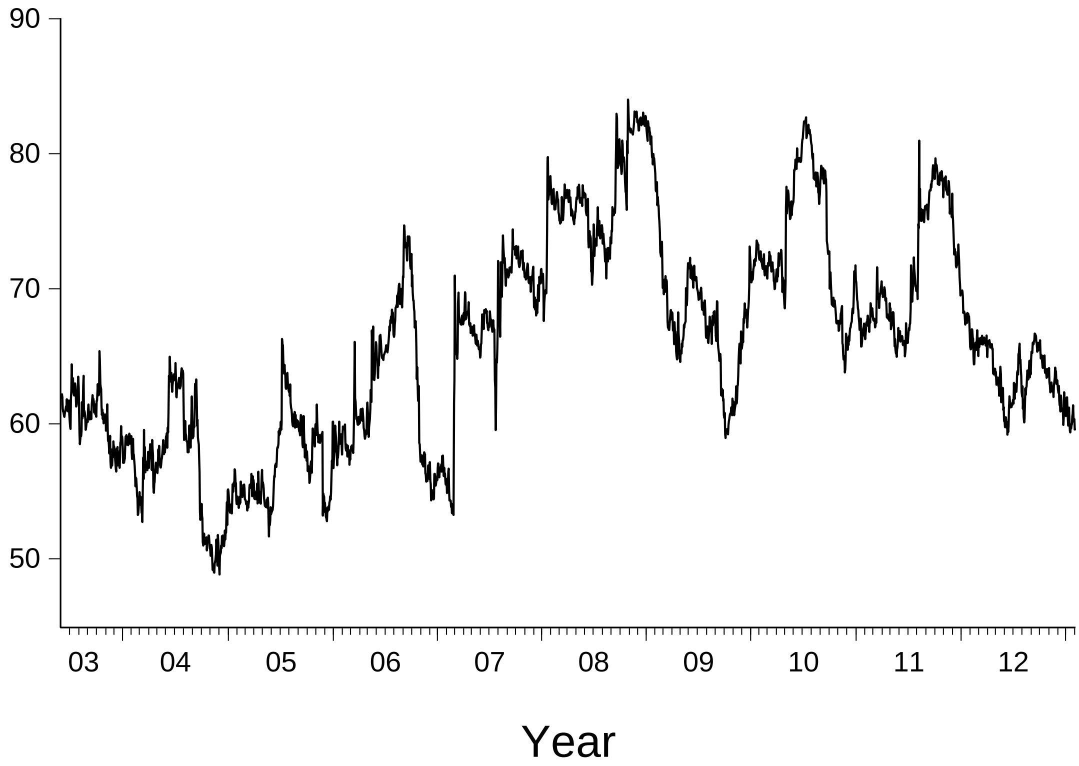

Figure 3: Total Volatility Connectedness Index
The rolling estimation window width is 200 days, and the predictive horizon for the underlying variance decomposition is 12 days

turn our interest to directional volatility indices to quantify the role of countries in volatility transmission during the crisis.

6.2.1 Total Connectedness

In this section, we analyze the movements of the total connectedness index which can be viewed as a systemic risk indicator. Figure 3 depicts the index from 2004 to 2013. By construction, the total connectedness index tells what fraction of the total volatility shock in the global banking system is due to shocks transmitted from other countries. Total volatility in the system is normalized to 100, so the index is out of 100. To exemplify, we can interpret the index number of 80 in a way that 20 percent of volatility in the system is explained by own volatility shocks, whereas 80 percent of volatility is explained due to shocks transmitted from other countries. In this regard, the number indicates how connected the banking systems are in selected countries, therefore, the risk in the whole system.

A cursory look at the total connectedness index suggests two distinct time period. The first period covers the period from December 2003 to the end of 2005. Over this period, the index hovered in the 50-70 range and never exceeded a certain level. Moreover, there is no particular trend in this period and fluctuations can be associated with individual events. For example, the highest point the index touched between 2004 and 2006 realized with a spike on 7 July 2005 in which a series of coordinated suicide attacks hit London. On the other hand, the second highest point was reached more gradually in June-July 2004 during which the Fed ended the low interest rate era that began in 2001 as a response to the burst of the dot-com bubble. In June 2004, Fed raised interest rate for the first time in more than four years and continued to raise it in the subsequent policy meetings.

However, from the beginning of 2006, the index started to increase and moved to a new territory ranged between 60 and 80. Obviously, this period corresponds to the run-up to the recent global financial crises. Over 2006, there was a trend starting from fifty and ending with a peak of 75 in September of the same year. This shows that the impact of the crisis became gradually apparent in the index before it reached its climax. This point particularly deserves attention because in 2006, there was no sign of a financial crisis except for a slight slowdown in the US housing market. Throughout the year, the Fed continued to increase its policy rate until September 2006.

In 2007 and 2008, the index exhibited a step by step increase with four spikes. However, contrary to pre-crisis period, after each spike, the connectedness index did not fall again and remained steady around its new level. This means that the risk accumulated through individual events did not go away in the following periods. With these four jumps, index rose from around 50 to 85 gradually. Given that the first serious sign of the financial crisis appeared in 2007 before reaching its peak at the end of 2008 with Lehman Brothers bankruptcy, the index reflects the evaluation of the crisis with its "jump and stay there" characteristic. To see the underlying reasons behind each spike in this period, we will examine them separately. The first spike corresponds to Chinese stock market bubble crash on 27 February 2007 in which the SSE Composite Index of the Shanghai Stock Exchange plunged by 9 percent, the largest drop in the last ten years. The effect of the burst did not remain limited to China and Asia. It spread rapidly to the other financial markets around the world. Dow Jones industrial average fell % 3,3 , its biggest point drop since September 11 terrorist attack and all European stock markets has slumped. As the slowdown in the housing market accelerated, this period also coincided with the first concerns over economic growth.

The second jump of the index in July-August 2007 is relatively small and more gradual compared to the first spike. But, it can be considered more important in the sense that it shows the first sign of problems in the subprime mortgage market, the primary reason of the financial crisis. Despite some worries about the subprime mortgage market, in 2007, it became apparent that the extent of the crisis was beyond what it had been thought to be as the problems spread beyond the United States' borders. For example, in June 2007, rating agencies downgraded more than hundred bonds backed by mortgage securities. Soon after, Bear Stearns liquidated its two hedge funds invested heavily in mortgage backed securities. The announcement of the BNP Paribas that it would halt activities of three hedge funds specialised in mortgage market was the peak of the crisis. After the announcement, the interbank market has frozen completely as libor-ois spread increased from 10 basis points to 90 basis points. Outside the US, Northern Rock, a British bank, applied to the Bank of England for emergency funding as a result of liquidity problems. Following these developments, on 18th September 2007, Fed started to ease its monetary policy.

The third spike, the steepest one, was associated with the global stock market downturn of January 2008. Due to the significant risk of a recession in the US economy, money started to escape to the safe havens and it triggered stock market crashes in many countries. The Fed countered the pressure with the further interest rate cuts. The index reached all-time high in August-September 2008 period which is symbolised with the Lehman Brothers bankruptcy. Although the Lehman bankruptcy can be seen as the climax of the crisis, it was not the only troubled financial institution in that period. Over September 2008, the takeover of Fannie Mae and Freddie Mac by the US government, the takeover of Merrill Lynch by Bank of America Merrill Lynch, the rescue fund of 85 billion given to AIG and 700 billion proposal of bailout bill can be counted among the most important events of this period. Therefore, our already-high connectedness index rose gradually and reached its peak at the end of September 2008.

So far, we have focused on the developments in the run-up to the financial crisis by associating them with the movements of the total connectedness index. In the remaining part of this section, our attention will be directed to explain the performance of the index following the peak of the crisis. Remaining steady around an all-time high level, the index started to decline due to the perception that the worst was behind as financial conditions improved. Until the end of 2009, most policy makers and market participants held a more optimistic view of the world economy. As a result of this atmosphere, stock markets around the world started to climb. Even some central banks began to raise their policy rates concerning price increases in commodity markets and announcing the end of the crisis. In line with these optimistic views, our index, except for a few short time periods, fell gradually during 2009. Nevertheless, in late 2009, the focus of the crisis switched from the banking sector to sovereign debt market, particularly with the increase of bond yields of some European countries. After dropping to the lowest point since the economic crisis began, total connectedness index started to increase gradually in October 2009. It remained steady around seventy in the first four months of 2010 due to continuing concerns about Eurozone. However, Greece shock led to index to jump ten points in a few days. After several austerity measures adopted by Greek government, on 9 May 2010 the IMF and the European Union announced that they would provide financial assistance to Greece whose sovereign bond spread reached unprecedented level. This was the first international measure in connection with the sovereign debt crisis.

After fluctuating around a high level during the subsequent two months, index dropped sharply to 70 points. It remained around this level without further drops in the next six months, reflecting the concern about European banking and debt crisis. In the second half of 2011, crisis became more severe with the increase in bond spreads of Italy and Spain, whose economies are much larger compared to those who had financial problems before. As a result of these development "too big to fail" phenomena started to apply to sovereigns as well as financial institutions. This exacerbated the problems in Europe by leading the global crisis to enter a new stage. Unlike the Greece case, increase in the index was not steep and have lasted more than five months reflecting the financial turmoil all around the world. In this period we also see one day spike on 9 August 2010 because Standard and Poor's downgraded US bond from the highest grade to one notch below. In addition to that, we can also see the effects of Fukishima nuclear disaster by another one day increase in index on 15 March 2011. In late 2011 and in the first half of 2012, index fell below 60 which was last seen in 2009 before the European sovereign debt crisis. We see a rise again starting from July 2012 but the rise was stopped by announcement of governor of European Central Bank Mario Diraghi. The commitment that the ECB is ready to buy government bonds of the insolvent countries to save the Euro eased the stress in the market and financial risks declined all over the world. In this period, like in 2009, positive views on the world economy outweighed negative ones, hence index dropped to the level around which it was in 2009. Lastly, we see some increase in the last part of the graph which probably identifies the concern over the US budget deficit, so-called fiscal cliff.

6.2.2 Directional Connectedness

This part of the study investigates the directional volatility connectedness using dynamic rolling window analysis. The "net", "to", and "from" directional connectedness tables are presented in Figure 4, Figure 5 and Figure 6 respectively. In each figure, we have fourteen graphs attached to each country in our sample. Since these graphs involve a large amount of information, we restrict ourselves to "net" connectedness which can be viewed as the net influence of a country on global volatility transmission over the last decade. The sign of the index tells

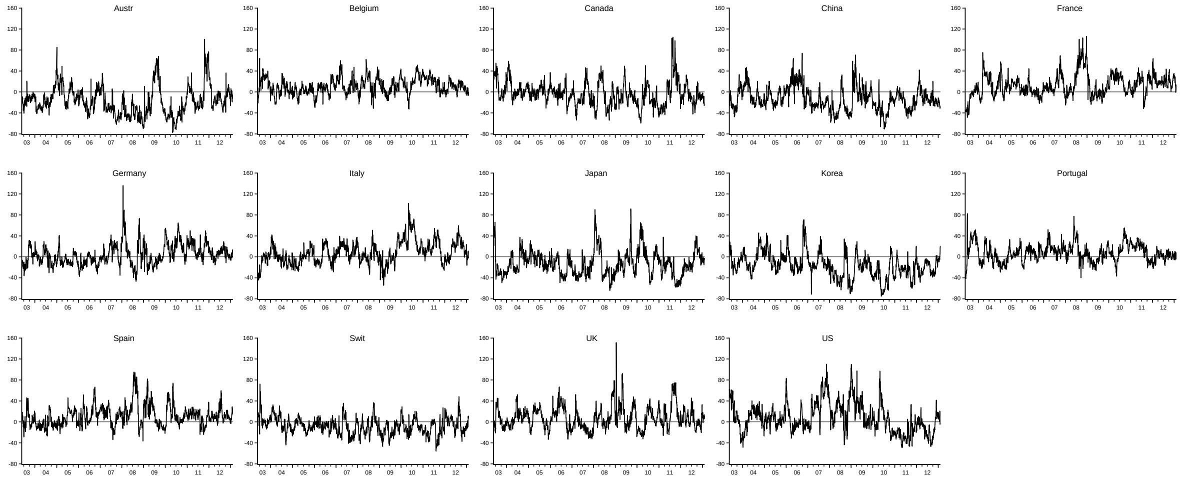

Figure 4: Net Directional Connectedness Indices

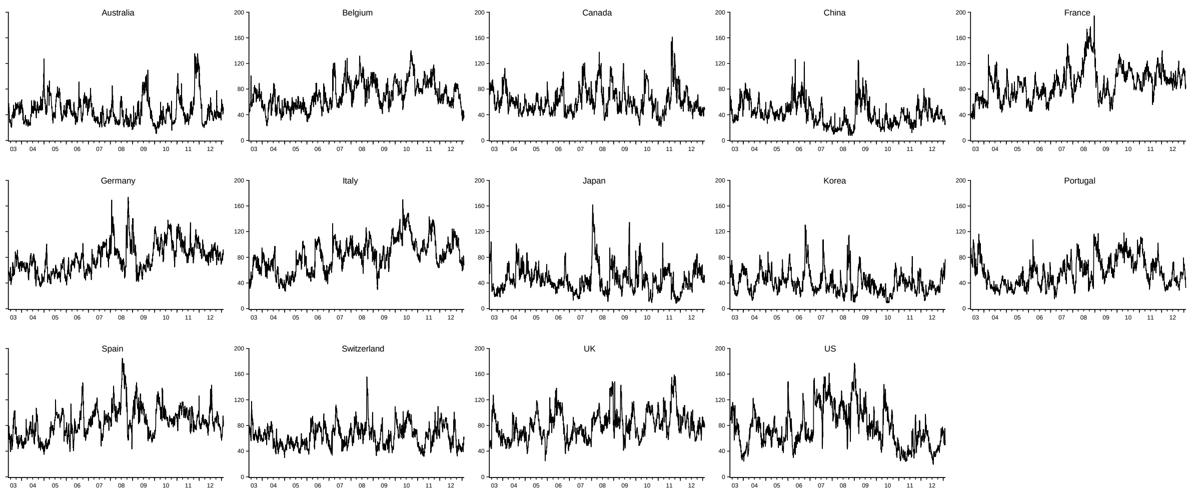

Figure 5: To Directional Connectedness Indices

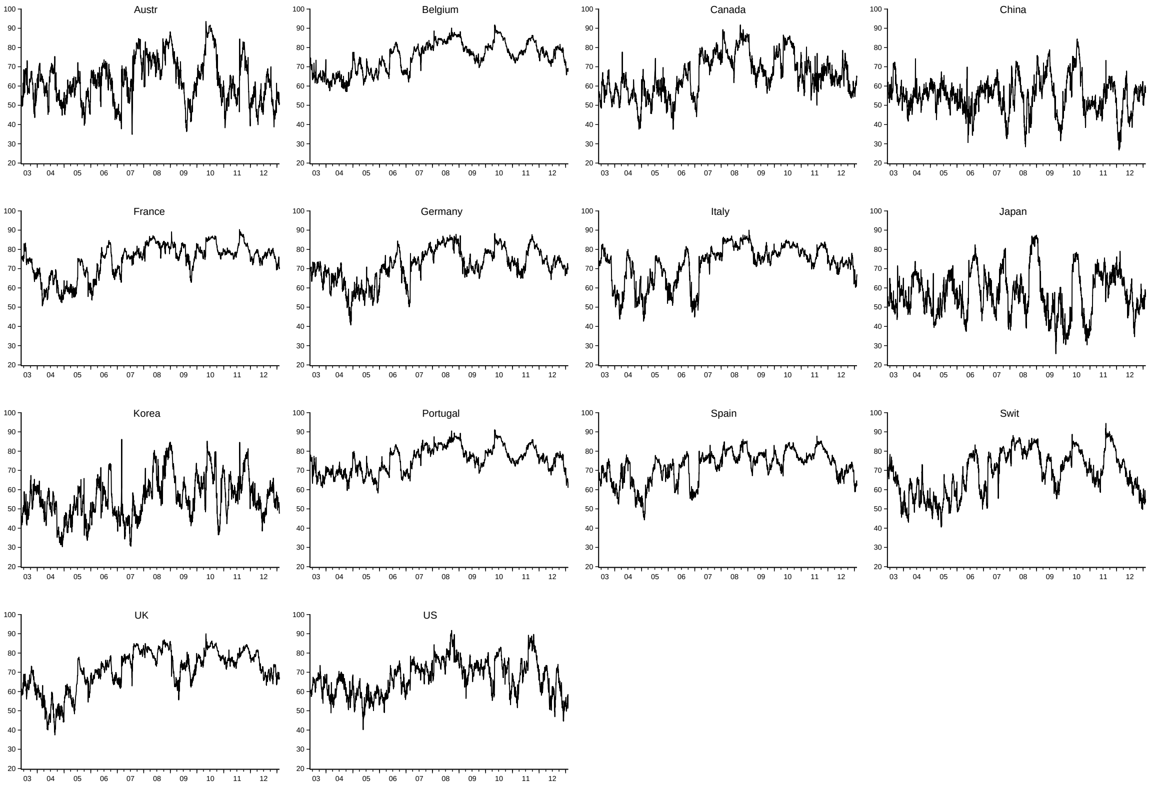

Figure 6: From Directional Connectedness Indices

whether the country is a net receiver or a net transmitter of the volatility shock. When we look at the trend throughout the sample, some countries, on average, remain above the zero line, whereas some move below the zero line. Larger European countries, Germany, Italy, Spain, UK, France and the US generate volatility shocks in line with static connectedness analysis. However, once the first sign of the crisis emerged, we started to see a stronger decoupling across financial markets. On the one side, net connectedness of the US and the European countries started to increase further. On the other side, "net" connectedness of the countries outside of the epicentre of the crisis, in particular Asian countries, went deeper into the negative territory. This observation reflects the fact that crisis originated in US subprime mortgage market and spread to Europe due to high exposition of European financial institutions to US mortgage-based assets. Nevertheless, the influence of the US and the European countries is not homogeneous over time. At the beginning of the crisis, the net volatility connectedness of the US jumped to the unprecedented level as a result of the troubles in subprime mortgage markets.

Moreover, it continued to fluctuate around this level for a certain time period. However, as the focus of financial markets switched to sovereign debt problems of some European countries, the US' "net" connectedness fell to its pre-crisis level as those of European countries started to rise. From 2010 onwards, almost all European countries' "net" volatility connectedness stayed in the positive region with occasional jumps.

7 Conclusion

Recent financial crisis have drastically changed what we had known about the systemic risk and its transmission. Due to the strong links across financial markets, what seemed to be a country-specific problem at the onset of the crisis transformed itself into a crisis on a global scale and led to a "once in a hundred years" recession. Hence, uncovering the transmission mechanism of the systemic risk gained unprecedented importance to prevent similar crises from happening in the future.

In this paper, we seek to contribute to risk measurement literature by incorporating a dynamic factor model into the Diebold-Yilmaz connectedness framework. The goal of the paper is twofold. First, exploiting dynamic factor model analysis, we can eliminate the limitation on the number of variables that can be included in DY framework. This improvement allows us to exploit larger dimensional datasets in risk measurement analysis. Second, contrary to dominant approach in the literature we measure the systemic risk at the country level rather than the institutional level. In order to see volatility transmission mechanism across countries at full length, we carry out both dynamic and static analyses. In the dynamic analysis, we developed the total connectedness index as a systemic risk measurement indicator. In addition to total systemic risk, the dynamics of fourteen banking systems are presented through "to", "from" and "net" connectedness indices attached to each country. On the other hand, to obtain the contribution of each country to the connectedness over the last decade, we carry out static analysis with full sample data.

Our results provide important results on how banking systems around the world are connected to each other before, during and after the financial crisis. First, in the light of the evaluation of our total connectedness index, we are able to track the major phases of the global financial crisis. We also find that European countries and the US are the main sources of volatility shocks over the entire sample. However, with the outbreak of the crisis, these countries began to play more dominant role in transmitting volatility. At the early stages of the crisis, from 2007 through

2009, US banking system is at the root of global volatility shocks. But, from 2009 onwards European countries took the role of the US. Over this period, Asian countries, Japan, China and Korea, are net main receiver of connectedness, reflecting the fact that they are highly exposed to the developments in the countries where the crisis is originated and intensified. Our results also suggest that regional ties have significant effect on volatility transmission. Connectedness across countries located in the same region seems to be higher compared to those of other countries.

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A Bank List

Country	Asset to Gdp (Percent)	GDP	Number of Banks	Currect Account Openness
Australia	201	1,400	11	1.12
Belgium	324	510	4	2.44
Canada	200	1,700	16	2.44
China	NA	7,300	15	-1.17
France	334	2,800	7	2.44
Germany	308	3,600	6	2.44
Italy	177	2,200	13	2.44
Japan	192	5,900	69	2.44
Korea, Rep.	153	1,100	5	0.94
Portugal	300	240	3	2.44
Spain	368	1,500	7	2.44
Switzerland	483	660	12	2.44
United Kingdom	535	2,400	7	2.44
United States	84	15,000	33	2.44

Table 3: Descriptive Statistics

Current Account Openness Indices are taken from Chinn and Ito (2008). All GDP numbers are in billion of US dollars.

Ticker	Name	Mcap(5/02/2013)	Mcap(2/5/2007)	Variance Explained
NAB-AU	NATIONAL AUSTRALIA BANK LIMITED	68,353	59,522	0.67
CBA-AU	COMMONWEALTH BANK OF AUSTRALIA	107,969	57,521	0.65
ANZ-AU	AUSTRALIA AND NEW ZEALAND BANKING GROUP LIMITED	76,988	46,834	0.66
WBC-AU	WESTPAC BANKING CORPORATION	90,639	42,023	0.63
MQG-AU	MACQUARIE GROUP LIMITED	13,116	18,615	0.51
AMP-AU	AMP LIMITED	16,306	16,835	0.40
ASX-AU	ASX LIMITED	6,604	6,764	0.37
CPU-AU	COMPUTERSHARE LIMITED	5,780	5,241	0.20
PPT-AU	PERPETUAL LIMITED	1,707	2,729	0.35
BEN-AU	BENDIGO AND ADELAIDE BANK LIMITED	3,969	1,819	0.45
BOQ-AU	BANK OF QUEENSLAND LIMITED	2,806	1,704	0.38

Table 4: Australian Banks

Market capitalizations are in billions of US dollars. Current mcap gives the market capitalization values of corresponding banks on Feb 5, 2013. Pre-crisis mcap gives the market capitalization values of banks on May 2, 2007. Company tickers and market capitalization are taken from Thomson ONE Analytics. The last column gives percentage of variance explained by country factor.

Ticker	Name	Mcap(5/02/2013)	Mcap(2/5/2007)	Variance Explained
KBC-BT	KBC Groupe S.A.	14,850	49,039	0.83
DEXB-BT	DEXIA S.A.	105	38,428	0.75
KBCA-BT	KBC ANCORA C.V.A.	1,566	9,429	0.75
BNB-BT	Banque Nationale de Belgique S.A.	1,407	1,990	0.17

Table 5: Belgian Banks

Market capitalizations are in billions of US dollars. Current mcap gives the market capitalization values of corresponding banks on Feb 5, 2013. Pre-crisis mcap gives the market capitalization values of banks on May 2, 2007. Company tickers and market capitalization are taken from Thomson ONE Analytics. The last column gives percentage of variance explained by country factor.

Ticker	Name	Mcap(5/02/2013)	Mcap(2/5/2007)	Variance Explained
RY-T	THE ROYAL BANK OF CANADA	9,078	6,622	0.69
BNS-T	THE BANK OF NOVA SCOTIA	6,997	4,718	0.71
TD-T	The Toronto-Dominion Bank	7,636	4,417	0.69
BMO-T	BANK OF MONTREAL	4,111	3,092	0.70
CM-T	CANADIAN IMPERIAL BANK OF COMMERCE	3,337	3,012	0.70
TRI-T	THOMSON REUTERS CORPORATION	2,537	2,815	0.47
BAM'A-T	BROOKFIELD ASSET MANAGEMENT INC.	2,364	2,392	0.41
IGM-T	IGM FINANCIAL INC.	1,087	1,268	0.44
NA-T	NATIONAL BANK OF CANADA	1,275	902	0.63
OCX-T	ONEX CORPORATION	504	446	0.39
CIX-T	CI Financial Corp.	773	342	0.44
AGF'B-T	AGF MANAGEMENT LIMITED	107	309	0.37
CWB-T	Canadian Western Bank	247	134	0.30
DC'A-T	DUNDEE CORPORATION	175	113	0.31
HCG-T	HOME CAPITAL GROUP INC.	208	112	0.18
LB-T	LAURENTIAN BANK OF CANADA	125	68	0.44

Table 6: Canadian Banks

Market capitalizations are in billions of US dollars. Current mcap gives the market capitalization values of corresponding banks on Feb 5, 2013. Pre-crisis mcap gives the market capitalization values of banks on May 2, 2007. Company tickers and market capitalization are taken from Thomson ONE Analytics. The last column gives percentage of variance explained by country factor.

Ticker	Name	Mcap(5/02/2013)	Mcap(2/5/2007)	Variance Explained
600036-SH	China Merchants Bank Co., Ltd.	40,752	30,432	0.59
600030-SH	CITIC Securities Company Limited	24,196	22,857	0.67
600016-SH	CHINA MINSHENG BANKING CORP., LTD.	42,424	17,170	0.57
600000-SH	SHANGHAI PUDONG DEVELOPMENT BANK CO., LTD.	35,933	15,206	0.60
000001-SZ	Ping An Bank Co., Ltd.	17,979	6,535	0.57
000562-SZ	Hong Yuan Securities Co., Ltd.	6,616	2,928	0.66
600837-SH	HAITONG Securities Company Limited	16,563	2,191	0.58
600109-SH	SINOLINK SECURITIES CO., LTD.	3,826	1,475	0.48
000783-SZ	Changjiang Securities Company Limited	4,157	1,475	0.61
600816-SH	ANXIN TRUST INVESTMENT CO.,LTD	1,139	1,434	0.42
000563-SZ	SHAANXI INTERNATIONAL TRUST CO., LTD.	1,449	831	0.56
000728-SZ	GUOYUAN SECURITIES COMPANY LIMITED	3,850	596	0.60
000686-SZ	Northeast Securities Co., Ltd.	2,938	341	0.52
000776-SZ	GF Securities Co., Ltd.	15,764	246	0.49
600369-SH	Southwest Securities Co., Ltd.	3,795	88	0.28

Table 7: Chinese Banks

Market capitalizations are in billions of US dollars. Current mcap gives the market capitalization values of corresponding banks on Feb 5, 2013. Pre-crisis mcap gives the market capitalization values of banks on May 2, 2007. Company tickers and market capitalization are taken from Thomson ONE Analytics. The last column gives percentage of variance explained by country factor.

Ticker	Name	Mcap(5/02/2013)	Mcap(2/5/2007)	Variance Explained
BNP-FR	BNP PARIBAS S.A.	74,559	109,581	0.84
GLE-FR	SOCIETE GENERALE S.A.	33,251	97,355	0.84
ACA-FR	CREDIT AGRICOLE SA	23,518	69,753	0.80
KN-FR	NATIXIS S.A.	11,670	33,667	0.62
CC-FR	CREDIT INDUSTRIEL ET COMMERCIAL S.A.	5,608	14,767	0.07
CAF-FR	CAISSE REGIONALE DE CREDIT AGRICOLE MUTUEL ET D'ILE	684	1,159	0.08
CNF-FR	CAISSE REGIONALE DE CREDIT AGRICOLE MUTUEL NORD	326	579	0.11

Table 8: French Banks

, Market capitalizations are in billions of US dollars. Current mcap gives the market capitalization values of corresponding banks on Feb 5, 2013. Pre-crisis mcap gives the market capitalization values of banks on May 2, 2007. Company tickers and market capitalization are taken from Thomson ONE Analytics. The last column gives percentage of variance explained by country factor.

Ticker	Name	Mcap(5/02/2013)	Mcap(2/5/2007)	Variance Explained
DBK-XE	DEUTSCHE BANK AKTIENGESELLSCHAFT	46,778	80,199	0.70
CBK-XE	COMMERZBANK Aktiengesellschaft	11,711	32,834	0.71
COM-XE	comdirect bank Aktiengesellschaft	1,633	2,525	0.27
ARL-XE	Aareal Bank AG	1,383	2,290	0.57
DRN-XE	DAB Bank AG	482	894	0.26
GLJ-XE	GRENKELEASING AG	969	670	0.20

Table 9: German Banks

Market capitalizations are in billions of US dollars. Current mcap gives the market capitalization values of corresponding banks on Feb 5, 2013. Pre-crisis mcap gives the market capitalization values of banks on May 2, 2007. Company tickers and market capitalization are taken from Thomson ONE Analytics. The last column gives percentage of variance explained by country factor.

Ticker	Name	Mcap(5/02/2013)	Mcap(2/5/2007)	Variance Explained
UCG-MI	UniCredit, Societa per Azioni	33,540	107,623	0.78
ISP-MI	Intesa Sanpaolo SpA	29,066	99,719	0.66
MB-MI	Mediobanca Banca di Credito Finanziario Societa per Azioni	5,774	19,163	0.62
BMPS-MI	Banca Monte dei Paschi di Siena S.p.A.	3,643	16,616	0.66
BP-MI	Banco Popolare Societa cooperativa	3,364	12,558	0.74
PMI-MI	Banca Popolare di Milano - Societa cooperativa a responsabilita	2,224	6,901	0.69
CRG-MI	Banca Carige S.p.A. - Cassa di Risparmio di Genova e Imperia	2,131	6,339	0.46
CE-MI	Credito Emiliano S.p.A.	1,895	4,730	0.58
CVAL-MI	Banca Piccolo Credito Valtellinese, Societa cooperativa	730	1,897	0.43
BDB-MI	Banco di Desio e della Brianza Societa per Azioni	332	1,527	0.19
PEL-MI	Banca Popolare dell'Etruria e del Lazio - Societa cooperativa	184	1,192	0.58
BFE-MI	Banca Finnat Euramerica S.p.A.	138	506	0.13
BSRP-MI	Banco di Sardegna S.p.A.	70	189	0.22

Table 10: Italian Banks

Market capitalizations are in billions of US dollars. Current mcap gives the market capitalization values of corresponding banks on Feb 5, 2013. Pre-crisis mcap gives the market capitalization values of banks on May 2, 2007. Company tickers and market capitalization are taken from Thomson ONE Analytics. The last column gives percentage of variance explained by country factor.

Ticker	Name	Mcap(5/02/2013)	Mcap(2/5/2007)	Variance Explained
8306-TO	Mitsubishi UFJ Financial Group, Inc.	80,802	113,938	0.34
8411-TO	Mizuho Financial Group, Inc.	52,128	72,153	0.23
8316-TO	Sumitomo Mitsui Financial Group, Inc.	57,988	66,317	0.27
8308-TO	Resona Holdings, Inc.	11,364	26,762	0.28
8332-TO	The Bank of Yokohama, Ltd.	6,409	10,434	0.49
8309-TO	Sumitomo Mitsui Trust Holdings, Inc.	14,943	8,411	0.30
8355-TO	THE SHIZUOKA BANK, LTD.	6,388	7,704	0.51
8331-TO	The Chiba Bank, Ltd.	5,381	7,687	0.46
8354-TO	Fukuoka Financial Group, Inc.	3,563	5,626	0.43
8333-TO	The Joyo Bank, Ltd.	3,697	5,276	0.54
8377-TO	Hokuhoku Financial Group, Inc.	2,250	4,553	0.35
8369-TO	The Bank of Kyoto, Ltd.	3,151	4,110	0.49
8359-TO	The Hachijuni Bank, Ltd.	2,594	3,956	0.51
8327-TO	THE NISHI-NIPPON CITY BANK, LTD.	2,175	3,595	0.38
8334-TO	The Gunma Bank, Ltd.	2,242	3,455	0.54
8379-TO	The Hiroshima Bank, Ltd.	2,644	3,425	0.43
8385-TO	The Iyo Bank, Ltd.	2,545	3,324	0.50
8418-TO	Yamaguchi Financial Group, Inc.	2,559	3,310	0.45
8358-TO	Suruga Bank Ltd.	3,499	3,189	0.40
8382-TO	The Chugoku Bank, Limited	3,106	3,131	0.42
8341-TO	The 77 Bank, Ltd.	1,720	2,591	0.42
8356-TO	The Juroku Bank,Ltd.	1,332	2,275	0.45
8336-TO	The Musashino Bank, Ltd.	1,122	1,876	0.41
8366-TO	THE SHIGA BANK, LTD.	1,455	1,874	0.40
8386-TO	The Hyakujushi Bank, Ltd.	1,225	1,839	0.49
8368-TO	The Hyakugo Bank, Ltd.	1,091	1,777	0.48
8381-TO	The San-in Godo Bank, Ltd.	1,306	1,739	0.43
8544-TO	The Keiyo Bank, Ltd.	1,420	1,734	0.39
8394-TO	The Higo Bank, Ltd.	1,403	1,704	0.45
8324-TO	The Daishi Bank, Ltd.	1,305	1,606	0.47
8390-TO	THE KAGOSHIMA BANK,LTD.	1,361	1,580	0.44

8363-TO	The Hokkoku Bank, Ltd.	1,357	1,540	0.43
8421-TO	Shinkin Central Bank	1,275	1,501	0.05
8522-TO	The Bank of Nagoya, Ltd.	725	1,434	0.41
8367-OK	The Nanto Bank, Ltd.	1,234	1,433	0.36
8339-TO	The Tokyo Tomin Bank, Limited	392	1,403	0.39
8361-TO	The Ogaki Kyoritsu Bank, Ltd.	1,150	1,348	0.44
8388-TO	The Awa Bank, Ltd.	1,396	1,310	0.48
8415-TO	Kiyo Holdings, Inc.	1,093	1,308	0.28
8360-TO	The Yamanashi Chuo Bank,Ltd.	758	1,244	0.41
8527-TO	The Aichi Bank,Ltd.	573	1,192	0.32
8345-TO	The Bank of Iwate, Ltd.	795	1,118	0.30
8392-TO	THE OITA BANK, LTD.	604	1,018	0.38
8343-TO	THE AKITA BANK, LTD.	540	954	0.38
8346-TO	The Toho Bank, Ltd.	791	940	0.39
8543-OK	THE MINATO BANK, LTD.	726	931	0.28
8387-TO	The Shikoku Bank, Ltd.	554	911	0.36
8344-TO	The Yamagata Bank, Ltd.	775	911	0.33
8536-TO	The Higashi-Nippon Bank,Limited	447	818	0.33
8396-TO	The Eighteenth Bank, Limited	478	815	0.31
8397-TO	The Bank of Okinawa, Ltd.	830	814	0.27
8399-TO	Bank of The Ryukyus, Limited	505	806	0.32
8362-TO	The Fukui Bank, Ltd.	480	758	0.36
8550-TO	THE TOCHIGI BANK, LTD.	473	755	0.33
8342-TO	The Aomori Bank, Ltd.	631	725	0.38
8337-TO	The Chiba Kogyo Bank,Ltd.	411	680	0.32
8530-TO	The Chukyo Bank, Limited	475	679	0.27
8325-TO	The Hokuetsu Bank, Ltd.	571	673	0.37
8374-TO	The Mie Bank, Ltd.	305	654	0.33
8393-TO	The Miyazaki Bank, Ltd.	444	628	0.34
8395-TO	THE BANK OF SAGA LTD.	400	619	0.37
8541-TO	The Ehime Bank, Ltd.	447	595	0.29
8529-TO	The Daisan Bank,Ltd.	349	589	0.24

8350-TO	THE MICHINOKU BANK, LTD.	331	531	0.31
8338-TO	Tsukuba Bank, Ltd.	316	526	0.26
8558-TO	THE TOWA BANK,LTD.	359	481	0.18
8364-TO	THE SHIMIZU BANK,LTD.	278	430	0.29
8551-TO	The Kita-Nippon Bank, Ltd.	234	393	0.20
8521-TO	THE NAGANO BANK, LTD.	181	324	0.27
8562-TO	THE FUKUSHIMA BANK, LTD.	239	265	0.13
8563-TO	THE DAITO BANK, LTD.	139	176	0.13

Table 11: Japanese Banks

Market capitalizations are in billions of US dollars. Current mcap gives the market capitalization values of corresponding banks on Feb 5, 2013. Pre-crisis mcap gives the market capitalization values of banks on May 2, 2007. Company tickers and market capitalization are taken from Thomson ONE Analytics. The last column gives percentage of variance explained by country factor.

Ticker	Name	Mcap(5/02/2013)	Mcap(2/5/2007)	Variance Explained
105560-SE	KB Financial Group Inc.	13,435	30,366	0.68
055550-SE	SHINHAN FINANCIAL GROUP CO.,LTD	17,144	21,857	0.66
053000-SE	WooriFinance Holdings Co.,Ltd.	9,083	20,140	0.67
004940-SE	KOREA EXCHANGE BANK	4,366	10,535	0.53
024110-SE	INDUSTRIAL BANK OF KOREA	6,002	8,055	0.60

Table 12: Korean Banks

Market capitalizations are in billions of US dollars. Current mcap gives the market capitalization values of corresponding banks on Feb 5, 2013. Pre-crisis mcap gives the market capitalization values of banks on May 2, 2007. Company tickers and market capitalization are taken from Thomson ONE Analytics. The last column gives percentage of variance explained by country factor.

Ticker	Name	Mcap(5/02/2013)	Mcap(2/5/2007)	Variance Explained
BCP-LB	BANCO COMERCIAL PORTUGUES, SA	2,853	15,073	0.68
BES-LB	Banco Espirito Santo, SA.	5,419	10,156	0.72
BPI-LB	BANCO BPI S.A.	2,384	6,458	0.74

Table 13: Portuguese Banks

Market capitalizations are in billions of US dollars. Current mcap gives the market capitalization values of corresponding banks on Feb 5, 2013. Pre-crisis mcap gives the market capitalization values of banks on May 2, 2007. Company tickers and market capitalization are taken from Thomson ONE Analytics. The last column gives percentage of variance explained by country factor.

Ticker	Name	Mcap(5/02/2013)	Mcap(2/5/2007)	Variance Explained
san-mc	BANCO SANTANDER, S.A.	83,134	111,049	0.69
bbva-mc	BANK BILBAO VIZCAYA ARGENTARIA, S.A.	52,522	85,620	0.70
pop-mc	BANCO POPULAR ESPANOL, SOCIEDAD ANONIMA	7,132	24,060	0.75
bto-mc	Banco Espanol de Credito S.A.	3,311	17,029	0.39
sab-mc	BANCO DE SABADELL, S.A.	7,027	13,929	0.56
bkt-mc	Bankinter, S.A.	2,822	6,964	0.72
bva-mc	BANCO DE VALENCIA, S.A.	855	5,968	0.36

Table 14: Spanish Banks

Market capitalizations are in billions of US dollars. Current mcap gives the market capitalization values of corresponding banks on Feb 5, 2013. Pre-crisis mcap gives the market capitalization values of banks on May 2, 2007. Company tickers and market capitalization are taken from Thomson ONE Analytics. The last column gives percentage of variance explained by country factor.

Ticker	Name	Mcap(5/02/2013)	Mcap(2/5/2007)	Variance Explained
UBSN-VX	UBS Inc.	66,281	136,274	0.78
CSGN-VX	Credit Suisse Group Ltd	39,191	95,113	0.67
BCVN-EB	Banque Cantonale Vaudoise	4,609	4,356	0.29
LLB-EB	Liechtensteinische Landesbank Aktiengesellschaft	1,072	3,369	0.19
SGKN-EB	Cantonal Bank of Saint Gall Ltd	2,392	2,938	0.10
VATN-EB	Valiant Holding AG	1,546	2,392	0.01
BSAN-EB	Bank Sarasin Co. Ltd	1,520	1,979	0.31
LUKN-EB	Luzerner Kantonalbank AG	3,337	1,926	0.07
VPB-EB	Verwaltungs- und Privat-Bank Aktiengesellschaft	418	1,355	0.16
BC-EB	Bank Coop Ltd	1,002	1,123	0.00
BLKB-EB	Basellandschaftliche Kantonalbank	702	640	0.02
BSKP-EB	Basler Kantonalbank	639	580	0.01

Table 15: Swiss Banks

Market capitalizations are in billions of US dollars. Current mcap gives the market capitalization values of corresponding banks on Feb 5, 2013. Pre-crisis mcap gives the market capitalization values of banks on May 2, 2007. Company tickers and market capitalization are taken from Thomson ONE Analytics. The last column gives percentage of variance explained by country factor.

Ticker	Name	Mcap(5/02/2013)	Mcap(2/5/2007)	Variance Explained
Hsba-ln	HSBC HOLDINGS PLC	206,481	215,294	0.76
Rbs-ln	THE ROYAL BANK OF SCOTLAND GROUP PUBLIC LIMITED COMPANY	32,544	123,966	0.84
Barc-ln	BARCLAYS PLC	56,676	94,096	0.82
Lloy-ln	LLOYDS BANKING GROUP PLC	57,443	65,323	0.81
Stan-ln	STANDARD CHARTERED PLC	63,781	42,412	0.64
CBG-LN	CLOSE BROTHERS GROUP PLC	2,353	2,876	0.23
PAG-LN	THE PARAGON GROUP OF COMPANIES PLC	1,375	1,263	0.25

Table 16: UK Banks

Market capitalizations are in billions of US dollars. Current mcap gives the market capitalization values of corresponding banks on Feb 5, 2013. Pre-crisis mcap gives the market capitalization values of banks on May 2, 2007. Company tickers and market capitalization are taken from Thomson ONE Analytics. The last column gives percentage of variance explained by country factor.

Ticker	Name	Mcap(5/02/2013)	Mcap(2/5/2007)	Variance Explained
C	CITIGROUP INC.	130,394	268,591	0.77
BAC	BANK OF AMERICA CORPORATION	128,585	226,371	0.76
JPM	JPMORGAN CHASE CO.	184,912	179,517	0.77
WFC	WELLS FARGO COMPANY	184,162	119,195	0.80
GS	THE GOLDMAN SACHS GROUP, INC.	71,018	89,655	0.66
MS	MORGAN STANLEY	46,179	88,910	0.73
AXP	AMERICAN EXPRESS COMPANY	67,770	74,574	0.74
RY	THE ROYAL BANK OF CANADA	91,144	66,178	0.58
USB	U.S. BANCORP	62,817	59,986	0.76
TD	The Toronto-Dominion Bank	76,608	44,086	0.60
BK	THE BANK OF NEW YORK MELLON CORPORATION	32,171	31,008	0.74
BMO	BANK OF MONTREAL	41,245	30,895	0.60
COF	CAPITAL ONE FINANCIAL CORPORATION	33,459	30,816	0.72
STI	SUNTRUST BANKS, INC.	15,490	30,103	0.75
CM	CANADIAN IMPERIAL BANK OF COMMERCE	33,466	30,049	0.59
PNC	THE PNC FINANCIAL SERVICES GROUP, INC.	33,444	25,669	0.78
RF	REGIONS FINANCIAL CORPORATION	11,219	24,672	0.69
SCHW	THE CHARLES SCHWAB CORPORATION	21,409	24,221	0.44
STT	STATE STREET CORPORATION	26,206	23,358	0.75
BBT	BB T CORPORATION	21,594	22,880	0.77
FITB US	FIFTH THIRD BANCORP	14,635	22,504	0.74
BBD	BANCO BRADESCO S.A.	34,002	21,892	0.31
IBN	ICICI BANK LIMITED	25,952	18,520	0.25
BLK	BLACKROCK, INC.	40,485	17,256	0.46
KEY	KEYCORP	8,922	14,158	0.78
MTB	M T BANK CORPORATION	13,319	12,183	0.70
AMTD	TD AMERITRADE HOLDING CORPORATION	10,673	10,428	0.27
CMA	COMERICA INCORPORATED	6,606	9,722	0.78
NYB	NEW YORK COMMUNITY BANCORP, INC.	5,989	5,439	0.53
DNB	THE DUN BRADSTREET CORPORATION	3,783	5,409	0.27
BAP	CREDICORP LTD.	11,543	5,164	0.15

RJF	RAYMOND JAMES FINANCIAL, INC.	6,288	3,704	0.66
CFR	CULLEN/FROST BANKERS, INC.	3,684	3,101	0.68

Table 17: US Banks

Market capitalizations are in billions of US dollars. Current mcap gives the market capitalization values of corresponding banks on Feb 5, 2013. Pre-crisis mcap gives the market capitalization values of banks on May 2, 2007. Company tickers and market capitalization are taken from Thomson ONE Analytics. The last column gives percentage of variance explained by country factor.