Network Risk: how network exposures affect banks' vulnerability

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Abstract

The recent financial crisis demonstrated the increasing importance of interrelations among financial institutions in terms of systemic risks. By means of a VAR model, we analyze the impact a financial institution has on the systemic risk vulnerability of its connected peers, in a multivariate financial network context. For this purpose, we first construct weekly rebalanced large and small portfolio indexes based on the capitalization level of financial institutions, to control for the size effect on the level of systemic risk. Then we estimate the individual institutions vulnerability level using marginal expected shortfall (MES) systemic risk measure, and we consider the institution interrelations using two MES alternatives: the network based MES (NetMES) and the Bayesian averaging of NetMES. Finally, we investigate if the VAR lead-lag relationship among the the large and small capitalization financial stocks is sustained within the systemic risk vulnerability series of MES, NetMES and Bayesian averaging of NetMES.

Keywords: Financial networks,lead-lag effect, MES, systemic risk, VAR.

1 Introduction

A healthy financial system is the backbone of economic progress (see among others Santomero, 1984; Bhattacharya and Thakor, 1993; Allen and Santomero, 1997, 2001; Berger and Bouwman, 2009; Scholtens and Van Wensveen, 2000; Covas and Haan, 2011). The financial system is characterised by a set of interrelations among institutions greater than in most industries and, moreover, increasing as was demonstrated during the recent financial crisis (Allen et al.,2012; De Bandt et al.,2012; Acemoglu, et al.,2015; Glasserman and Young, 2015).

An interrelation perspective on the financial system structure includes financial institutions, with linkages between them that may transfer and magnify financial stress during times of crisis (Billio et al., 2012). The endogenous correlation within a financial network is pointed out in several works (see e.g. Bank for International Settlement 1994; Kaufman 1994; Crockett 1997; George 1998; and Board of Governors of the Federal Reserve System 2001), several point out an exogenous microeconomic event trigger with a spillover diffusion effect between institutions (see e.g. Kaminsky and Schmukler 1999; Aharony and Swary 1996; Kaminsky and Reinhart 2000; and Kaufman 1994); others refer to a macroeconomic event that simultaneously bring out severe losses between institutions (Benoit et al., 2016). Even though the financial institutions connectivity is investigated in many works (see for example, Allen and Gale, 2000; Elliott et al., 2014; Nier et al., 2007; De Bruyckere et al., 2013; Leitner, 2005; Iyer and Peydro, 2011; Schnabl, 2012), the main focus is on systemic risk (see for example, Eisenberg and Noe, 2001; Summer, 2003; Lehar, 2005; Iori et al., 2006; Bartram et al., 2007; Patro et al., 2013; Bluhm and Krahnen, 2014; Teteryatnikova, 2014).

The objective of this paper is to assess the impact that a financial institution has on the systemic vulnerability of other financial participants within a network context. For this purpose, we use vector autoregressive (VAR) models to capture the directional systemic contagion (see Billio et al., 2012; Diebold and Yilmaz, 2014; Ahelegbey et al., 2016a,b). The autoregressive feature found in returns time series allows to model the volatility clustering (see Lo, 2001; Getmansky et al., 2004), with a consideration for the size effect (Hou, 2007), in which an intra-industry lead-lag relation is detected from big to small firms. Also, Lo and MacKinlay (1990) show the existence of a systematic lead-lag relationship among returns of large/small size-sorted portfolios. The study of the interaction between large/small-cap segments of financial institutions is in line with the size effect that such institution have on their associated risk vulnerability and contribution (see for example, Laeven et al., 2016).

2 Data and market indexes

To model interdependence between financial institutions, instead of using any existing market index for large and small capitalization stocks, we construct our own indexes. An already available index would be like a “black box”, as details like the constituents of the index, their weights in each distinct point of time and the re-balancing dates are unknown. Indeed, comparing the available market indexes, three separate causative influences can be uncovered. First, the behaviour of equity indexes is partly attributable to the technical procedures of its construction. Some indexes have a small number of stocks (less than thirty) while others have a large number. Some national markets are industrially concentrated while others are very diversified. These diversification elements explain part of the observed inter-market differences in price indexes behavior, that do not correspond to differences in the individual stocks behaviours. Second, nations vary in their industrial composition and have industries that are inherently more or less volatile. We can think of the index for a country as a managed portfolio, with particular industry sector “bets”. In this context, even a large portfolio can be influenced by disproportionate investments in certain industries. Third, exchange rates play a significant role. With returns expressed in a nations own (local) currency, part of a stock index return volatility is induced by monetary phenomena such as changes in anticipated and actual local inflation rates. Converting local currency returns into common currency returns (e.g., the U.S. dollar) does not entirely eliminate the exchange rates influence.

To construct our indexes, we collected stocks across the globe from Bloomberg LP based on two criteria; first, following the GICS classification, we select stocks which belong to the financial sector: banks and diversified financials, excluding consumer finance, diversified financial services, insurance and real estate companies[1]. We remark that, as the GICS classification is applied to companies around the world and it is annually revised, the universe is continuously up to date and, therefore, so will be our results. Second, we select stocks above a floor of $50 million capitalization, and we divide them in two tiers: top ones, the largest until reaching the 50% of market capitalization; and the remaining (bottom) ones. The sample contains the five world largest companies which account for 63.02% of 2010 world banking sector. In addition, the data provided are free of survivorship, restatement, and lagging bias. We then convert all stock prices in dollars. This because, according to Roll (1992), the best way to combine stocks in the same industry but traded in different currencies is to convert all returns first to a common currency and then construct the industry index. We then repeat the same data treatment Beginning from December 31, 2014 and going backwards to January 1, 2005, our portfolio is weekly rebalanced, ending up with 522 different groups of large and small capitalization financial stocks. Impac Mortgage Holdings is the stock with the lowest market capitalization, 1.7503 million, as of March 20, 2009 compared to 1.591 bn, as of January 7, 2005, and 59.253 million, as of December 26, 2014. During the coverage period, the indexes cover 2674 stocks, 1436 appeared in the weekly large cap portfolios, 2131 in the small cap portfolios and 893 moved between the two groups. The set of large cap stocks spans 99 countries, 3 industry groups, 5 industries, 8 sub-industries and 109 primary exchanges. For the small cap stocks, the corresponding numbers are: 108, 6, 9, 12 and 108 respectively. Only 193 of the 2131 small cap stocks survived through years. On the other hand, 321 large cap stocks survived through the years.

We can now calculate two return indexes as the market weighted average of the individual returns. The large cap return index considers, at each point in time, the top 50th percentile and the small cap return index considers the bottom 50th percentile. Table 1 presents the summary statistics of the constructed index returns. Both the skewness and the excess kurtosis statistics are significantly higher than that of the normal distribution at all meaningful significance levels. The results also suggest that both series are negatively skewed and leptokurtic, and that the small cap index returns (SCR) is more volatile than the large cap one (LCR), as expected. For LCR, the maximum positive change was 13.605% on November 2008 and the maximum drop -17.78% on

[1]Every stock in our considered database belongs to one of the three-digit subindustries.

October 2008. For SCR, the maximum positive change was 8.25% on May 2009 and the maximum drop -13.67% on October 2008. For both series the worst weekly change took place at the end of the second week on October 2008, when UniCredit, Italy s second biggest bank by market capitalization, was rumored to be insolvent and a large International Monetary Fund (IMF)-EU rescue package needed to stabilize the situation in Hungary, where the short-term swap and bond markets were frozen. The period with the highest increases was on April 2009, when the G20 and Japan announced a US$1-trillion and a US$150-billion economic stimulus packages, respectively, against the financial crisis.

Table 1 about here

3 Lead-lag effect of Index Returns

The integration of world financial markets has hastened due to the economic globalization and internet communication spreading effortless and immediately the price movements from one to another market. Thus, financial markets are more dependent on each other than ever before, and one market may lead the other market under some circumstances, yet the relationship may be reversed under other circumstances. Consequently, knowing how the markets are interrelated is of great importance. In the same way, for an investor or a financial institution holding multiple assets, the dynamic relationships between returns of the assets play a vital role in decision making. Furthermore, stock trades do not occur in a synchronous manner either different stocks are considered or a single stock since the trading intensity varies from hour to hour and from day to day. For example, consider stocks A and B that are independent and stock A is traded more frequently than stock B. For special news affecting the market that arrives near the closing hour on one day, stock A is more likely than B to show the effect of the news on the same day simply because A is traded more frequently. The effect of the news on B will eventually appear, but it may be delayed until the following trading day. If this situation indeed happens, return of stock A appears to lead that of stock B. Consequently, the return series may show a significant lag-1 cross-correlation from A to B even though the two stocks are independent. For a portfolio that holds stocks A and B, the prior cross-correlation would become a significant lag-1 serial correlation. For daily stock returns, non synchronous trading may introduce lag-one cross-correlation between stock returns, lag-one serial correlation in a portfolio return, and in sometimes negative serial correlations of the return series of a single stock. This important phenomenon described in the examples above is the lead-lag relationship that is seen sometimes between groups of stock returns. Lo and Mackinlay (1990) first document the existence of the lead-lag effect. Let LCR_t and SCR_t denote the returns of the large and the small cap index and let r_t a 2×1 vector containing the values of the returns series at date t. The dynamics of r_t are presumed to be governed by a 1^{st}-order Gaussian vector autoregressive model:

$$r_t = c + \Phi r_{t-1} + \epsilon_t \tag{1}$$

where $\epsilon_t \sim NIID(0, \Omega)$ is the error vector, $c \epsilon \Re^{2\times1}$ is the vector of intercepts, $\Phi \epsilon \Re^{2\times2}$ is the matrix of slopes. The VAR specification assumes that the next period's index return is linearly dependent on today's, with linear dependency captured by the slope matrix. The analytic representation of the VAR(1) defined above suggests the following regression model:

$$\begin{pmatrix} LCR_t \\ SCR_t \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{pmatrix} \begin{pmatrix} LCR_{t-1} \\ SCR_{t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_t^{large} \\ \epsilon_t^{small} \end{pmatrix} \tag{2}$$

3.1 Index returns lead-lag effect exercise

We consider weekly data of the large-cap and the small-cap index and we estimate the VAR [2]. The results are as follows (p-values appear in brackets below estimates):

$$\begin{aligned} \widehat{LCR}_t &= \underset{(0.5647)}{-0.0005} - \underset{(0.0009)}{0.0979} LCR_{t-1} + \underset{(0.0000)}{1.1904} SCR_{t-1} \quad \bar{R}^2 = 55.85\% \\ \widehat{SCR}_t &= \underset{(0.1587)}{0.0011} + \underset{(0.0015)}{0.1385} LCR_{t-1} + \underset{(0.0651)}{0.0183} SCR_{t-1} \quad \bar{R}^2 = 3.24\%. \end{aligned} \tag{3}$$

Studying the above estimated coefficients we draw a number of interesting conclusions. First, we confirm the lead-lag relation of DeMiguel et al. (2014) and Lo and MacKinlay (1990). More specifically, we observe that the large-cap returns lead the small-cap returns, since the large-cap interaction coefficient ϕ_{21} is statistically significant. Second, the autoregressive coefficients of the large cap stocks are statistically significant and positive. Our sample supports the result of DeMiguel et al. (2014) that the autoregressive coefficient of the small cap stocks are statistically significant. The small-cap returns are positively related to the returns in the large-cap segment of the stock market from the previous week ($\phi_{21} > 0$). From a biological perspective, this is characterized as a "complementary" relationship of large-cap stocks over the small-cap stocks.

We now present some robustness checks of our lead-lag effect exercise. Rolling analysis is used to evaluate the stability of the parameters identifying the periods where the interaction between the two different segments of the market was more intense. Rolling analysis is also useful to study if and how the direction of the interaction changes over time. Finally, with rolling analysis we can examine the evolution of the autoregressive coefficients through time. The VAR model is estimated using a 270-week window and then we test the significance of the autoregressive coefficients and the interaction terms of our VAR model. In Figure **??** and **??**, we present the time path of the estimated autoregressive coefficients and interaction terms. The gaps indicate the periods where they are not statistically significant. The large-cap autoregressive coefficient is statistically significant for almost the entire sample-period until March 2014. It is apparent that the coefficient ϕ_{11} is statistically positive for the entire sample period highlighting the existence of momentum in the large-cap segment of the market. The small-cap interaction term ϕ_{21} is statistically significant for the entire sample-period 2005-2014.

We expect the VAR coefficients to vary with time since the conditions in the financial markets have changed significantly from 2005 to 2014, especially because of the financial crisis of 2008. We estimate the VAR model splitting the sample period into two sub-periods each of which presents the period before and after the recent financial crisis (p-values appear in brackets below the estimates):

Table 2 about here

[2] We carried out the same exercise using monthly data. The results were broadly similar, and available upon request by the author.

4 Systemic Risk Lead-Lag Effect

Systemic risk is typically measured within a financial system comprised of a network of connected institutions, which may allow for the transfer of financial distress during times of financial crisis. Definitions of systemic risk point out the correlation and direct causation that endogenously exists within a network of financial institutions (see e.g. Bank for International Settlement 1994; Kaufman 1994; Crockett 1997; George 1998; and Board of Governors of the Federal Reserve System 2001). Other definitions point out an exogenous microeconomic event that diffuses with a spillover effect from specific business units to others (see e.g. Kaminsky and Schmukler 1999; Aharony and Swary 1996; Kaminsky and Reinhart 2000; and Kaufman 1994); or a macroeconomic event that causes simultaneous severe losses for market participants and diffuses through the system (Billio et al., 2012; Benoit et al., 2016).

However, systemic risk measures bivariate estimation overlook the network effect in estimating the risk level of a financial institution. To overcome this issue, Billio et al. (2012) introduce several econometric measures of connectedness based on principal component analysis and Granger-causality networks. In a related paper, Diebold and Yilmaz (2014) propose Vector Autoregressive models, augmented with a LASSO type estimation procedure, aimed at selecting the significant links in a network model. Similarly, Hautsch et al. (2014) and Peltonen et al. (2015) propose tail dependence network models. The previous models are based on the assumption of full connectedness among all institutions, which make their estimation and interpretation quite difficult, especially when a large number of them is being considered. To tackle this issue, Ahelegbey et al. (2016a) used Bayesian Graphical Models in conjunction with a structural vector autoregressive processes. Also, Giudici and Spelta (2016) have recently introduced correlation network models, which can fully account for partial connectedness, expressed in terms of conditional independence constraints. Barigozzi and Brownlees (2014) introduced multivariate Brownian processes with a correlation structure determined by a conditional independence graph. Correlation network models (see e.g. Giudici and Spelta 2016) can account for partial connectedness, expressed in terms of conditional independence constraints. They are based on graphical Gaussian models, which give them a stochastic background, and on Bayesian model averaging, which improves their robustness.

In this work, we investigate if the lead-lag relation that we found from large to small-cap returns manifests itself not only at the aggregate index return level, but also at the individual volatility level, using systemic risk indicators. In other words, we test whether a large-cap companies lead-lags small-cap ones, not only in terms of returns, as in the previous sections, but also in terms of risk. To estimate the risk exposure of an individual institutions to the market, we use the standard bivariate based marginal expected shortfall (MES) systemic risk measure, as well as two alternatives: the network based MES (NetMES) that extends MES taking multivariate dependences into account; and the Bayesian NetMES, that further accounts for network model uncertainty. Upon the estimation of the MES, NetMES and Bayesian NetMES, we rank institutions based on the systemic risk indicators in a descending order, from highest to lowest systemic risk level. We select the top six ranking institutions across the different systemic risk measures and sub-industries, and we test the lead-lag effect on the top six ranking institutions. We limit the test between large to small without considering the interrelations between different sub-industries within the same index.

4.1 Marginal expected shortfall (MES)

Acharya et al. (2010) introduced a measure for each bank's contribution to systemic risk namely Marginal Expected Shortfall (MES), defined as the expected return of bank i's shares conditional on the market realizing a return in the 5% tail. The rational of MES is close to the Too Interconnected To Fail logic (TIF) rather than to Too Big to Fail one (TBTF) (Banulescu and Dumitrescu, 2015). In our implementation of MES, we use the dynamic conditional correlation to take into account the increase in volatility during crisis times. To this aim, we will follow Brownlees and Engle (2012) and Engle (2012), who employ a bivariate GARCH model for the demeaned returns process, based on a Capital Asset Pricing Model (CAPM).

Consider a bivariate vector $r_t = (r_{it}, r_{mt})'$ that contains, at each time point, the returns of a sector and those of its reference market. Let H be its variance-covariance matrix, Brownlees and Engle (2012) and Engle (2012) propose that:

$$r_t = H_t^{1/2} \epsilon_t,$$

where $\epsilon_t = (\epsilon_{mt}, \eta_{it})$ represents a vector of *i.i.d.* zero mean innovations, and .

$$H_t = \begin{pmatrix} \sigma_{mt}^2 & \sigma_{mt}\, \sigma_{it}\, \rho_{it} \\ \sigma_{mt}\, \sigma_{it}\, \rho_{it} & \sigma_{it}^2, \end{pmatrix}$$

where σ_{mt} is the standard deviation of the reference market returns, σ_{it} is the standard deviation of the sector returns, and ρ_{it} is the correlation between the sector and the reference market returns. To estimate H_t, we use the dynamic conditional correlation model of Engle (2002) and Engle and Sheppard (2001). Once H_t is estimated, we can proceed with the estimation of the MES measure, which is a function of H_t. The MES measures the vulnerability of a banking sector i to the systemic risk originating from a financial market m. MES provides the one day loss expected if market returns are less than a given threshold C (in practice, it is assumed that $C = -2\%$). More precisely, MES is defined as a weighted function of tail expectations for the market residual and tail expectations for the banking sector residual, both calculated at time $t-1$, as follows:

$$MES_{it}(C) = \sigma_{mt}\, \rho_{it}\, \mathbb{E}_{t-1}(\varepsilon_{mt} | \varepsilon_{mt} < \frac{C}{\sigma_{mt}}) + \sigma_{it}\, \sqrt{1-\rho_{it}^2}\, \mathbb{E}_{t-1}(\eta_{it} | \varepsilon_{mt} < \frac{C}{\sigma_{mt}}). \tag{4}$$

The intuition behind higher values of MES is that the more vulnerable the institution is to systemic risk, the higher is its contribution to the risk of the financial system. As previously described, Engle (2012) model expresses returns as a function of the correlation between the market and the sector under consideration.

4.2 Network marginal expected shortfall (NetMES)

In highly correlated markets, such as financial ones, it could very well be the case that the correlation between the market and one sector's returns contains other effects, for example the correlation of the considered sector with another sector, or the correlation of the market with another sector's returns. To remove "spurious" effects, that may bias the correlation between the sector and the market returns, we replace marginal correlations with partial correlations: the correlations between the residuals from the regression of the sector returns on all other sector's, and the residuals from the regression of the market returns on all other sector's. In this way we obtain a "netted" estimate of H, not biased by spurious effects and, consequently, a "netted" estimate of the Marginal Expected Shortfall (NetMES). We follow the definition of NetMES as introduced by Hashem and Giudici (2016), to take interconnectedness into account in the estimation of MES.

More specifically, to estimate partial correlations, recall that by definition, the partial correlation coefficient $\rho_{ij.V}$ is equal to the correlation between the residuals from the regression of X_i on all other variables (excluding X_j) with the residuals from the regression of X_j on all other variables (excluding X_i) as in the following formula:

$$\rho_{ij.V} = corr(\,\varepsilon_{X_i|X_{V\setminus\{j\}}}, \varepsilon_{X_j|X_{V\setminus\{i\}}})$$

The partial correlation coefficient allows to measure the additional contribution of variable X_j to the variability of X_i that is not already explained by the other variables, and vice versa.

More specifically, we define two multiple regression equations for each market and banking sector return series, with the dependent variable of the first being the market return series r_{mt}, and the dependent variable of the second being the specified banking sector return series r_{i_1t}. Both dependent variables are regressed on a set of independent variables of $r_{i_2t}, ..., r_{i_nt}$ that represent the other banking sectors in the financial system, as in the following:

$$\begin{cases} r_{mt} = a_1 + \beta_2 r_{i_2t} + ... + \beta_n r_{i_nt} + \epsilon_{i_1t} \\ r_{i_1t} = a_1 + \beta_2 r_{i_2t} + ... + \beta_n r_{i_nt} + \epsilon_{mt} \end{cases} \tag{5}$$

where ϵ_{i_1t} and ϵ_{mt} are the residual vectors of the banking sector i_1 and the market m. We repeat this extraction process for each pair of market and banking sector returns time series (r_{mt}, r_{it}).

The residual pairs extracted in equation (5) can then be inserted in equation (4), giving rise to a different estimate of H and, consequently, of MES that is called NetMES, to emphasize both the fact that the new measure is "netted" from spurious correlations and also the fact that it is conditional on a graphical network model.

4.3 Bayesian network marginal expected shortfall (Bayesian NetMES)

We follow Hashem and Giudici (2016) and Giudici and Spelta (2016) as they improve the stability and the robustness of the results, by using a Bayesian averaging perspective. We average NetMES from the different graphical networks using a Bayesian graphical model specification.

A network is comprised from a set of financial institutions, that constitute the network nodes. Assuming a multivariate Gaussian model for the time series observations of N financial agents, the linkages between the nodes can be described by an adjacency matrix A, that has an $N \times N$ dimension with elements $a_{i,j}$, in which $a_{i,j} = 1$ when two nodes are correlated, and $a_{i,j} = 0$ when they are not correlated. Partial correlations can be estimated assuming that the same observations follow a graphical Gaussian model, in which the variance-covariance matrix Σ is constrained by the conditional independence described by a graph (see e.g. Whittaker 1990; Lauritzen 1996; or, from an econometric viewpoint, Corander and Villani 2006 and Carvalho and West 2007).

More formally, let $x = (x_1, ..., x_N) \in R^N$ be a $N-$dimensional random vector distributed according to a multivariate normal distribution $\mathcal{N}_N(\mu, \Sigma)$. We will assume throughout that the covariance matrix Σ is not singular. For an undirected graph, let $G = (V, E)$, with vertex set $V = \{1, ..., N\}$, and edge set $E = V \times V$, a binary matrix, with elements e_{ij}, that describes whether pairs of vertices are (symmetrically) linked between each other ($e_{ij} = 1$), or not ($e_{ij} = 0$). If the vertices V of a graph are put in correspondence with the random variables $X_1, ..., X_N$, the edge set E induces conditional independence on X via the so-called Markov properties (see e.g. Lauritzen 1996). More precisely, the pairwise Markov property determined by G states that, for all $1 \leq i < j \leq N$:

$$e_{ij} = 0 \Longleftrightarrow X_i \perp X_j | X_{V \backslash \{i,j\}};$$

this indicates that, the absence of an edge between vertices i and j is equivalent to independence between the random variables X_i and X_j, conditionally on all other variables $x_{V \backslash \{i,j\}}$.

In our context, all random variables are continuous and it is assumed that $X \sim \mathcal{N}_N(0, \Sigma)$. Let the elements of Σ^{-1}, the inverse of the variance-covariance matrix, be indicated as $\{\sigma^{ij}\}$. Whittaker (1990) proved that the following equivalence also holds:

$$X_i \perp X_j | X_{V \backslash \{i,j\}} \Longleftrightarrow \rho_{ijV} = 0$$

where

$$\rho_{ijV} = \frac{-\sigma^{ij}}{\sqrt{\sigma^{ii}\sigma^{jj}}}$$

denotes the ij-th partial correlation, that is, the correlation between X_i and X_j conditionally on the remaining variables $X_{V \backslash \{i,j\}}$. It can also be shown that the partial correlation coefficient ρ_{ijV} is equal to the correlation of the residuals from the regression of X_i on all other variables (excluding X_j) with the residuals from the regression of X_j on all other variables (excluding X_i)as in the following:

$$\rho_{ijV} = \left(\varepsilon_{X_i|X_{V \backslash \{j\}}}, \varepsilon_{X_j|X_{V \backslash \{i\}}} \right)$$

In other words, the partial correlation coefficient measures the additional contribution of variable X_j to the variability of X_i not already explained by the others, and vice versa.

A graphical Gaussian model is a Gaussian distribution constrained by a set of partial correlations equal to zero, which corresponds to variables whose additional contribution is not statistically significant. Mathematically, by means of the pairwise Markov property, given an undirected graph $G = (V, E)$, a graphical Gaussian model can be defined as the family of all N-variate normal distributions $\mathcal{N}_N(0, \Sigma)$ that satisfy the constraints induced by the graph on the partial correlations for all $1 \leq i < j \leq N$, as follows:

$$e_{ij} = 0 \Longleftrightarrow \rho_{ijV} = 0$$

In practice, the available data will be used to test which partial correlations are different from zero at the chosen significance level threshold α. This leads to the selection of a graphical model on which all inferences are conditioned and determined. A drawback of this approach is that results are conditional on a fixed graphical structure. To overcome this problem, and robustify the results, we employ a Bayesian model averaging approach, in which the results estimates are averages of those coming from different graphs, each with a weight that corresponds to the Bayesian posterior probability of the corresponding graph.

For the purpose of a Bayesian application, the first task is to derive the likelihood of a graphical network, and specify an appropriate probability distribution over all graphical networks. For a given a graph G, we consider a sample X of size n from a Gaussian probability distribution $P = \mathcal{N}_N(0, \Sigma)$, and let S be the observed variance-covariance matrix that estimates Σ. The graph G has a defined subset of vertices $A \subset N$, in which Σ_A denote the variance-covariance matrix of the variables in X_A, and has S_A as the corresponding observed variance-covariance submatrix. When the graph G is decomposable, the likelihood of the data, under the graphical Gaussian model specified by P, nicely decomposes as follows (see e.g. Giudici and Spelta 2016):

$$p(x|\Sigma, G) = \frac{\prod_{c\in\mathcal{C}} p(x_C|\Sigma_C)}{\prod_{s\in\mathcal{S}} p(x_S|\Sigma_S)}$$

where C and S respectively denote the set of cliques and separators of the graph G, and:

$$P(x_C|\Sigma_C) = (2\pi)^{-\frac{n*|C|}{2}} |\Sigma_C|^{-n/2} exp[-1/2tr\left(S_C\left(\Sigma_C\right)^{-1}\right)]$$

and similarly for $P(x_S|\Sigma_S)$. A convenient prior for the parameters of the above likelihood is the hyper inverse Wishart distribution. It can be obtained from a collection of clique specific marginal inverse Wisharts as follows:

$$l(\Sigma) = \frac{\prod_{c\in\mathcal{C}} l(\Sigma_C)}{\prod_{s\in\mathcal{S}} l(\Sigma_S)}$$

where $l(\Sigma_C)$ is the density of an inverse Wishart distribution, with hyper-parameters T_C and α, and similarly for $l(\Sigma_S)$. For the definition of the hyper-parameters here we follow Giudici and Spelta (2016) and let T_C and T_S be the sub-matrices of a larger matrix T_0 of dimension $N \times N$, obtained, in correspondence of the two complete sets of vertices C and S, assuming that $\alpha > N$. To complete the prior specification, for $P(G)$ we consider a uniform prior over all possible graphical structures. Dawid and Lauritzen (1993) show that, under the previous assumptions, the posterior distribution of the variance-covariance matrix Σ is a hyper Wishart distribution with $\alpha + N$ degrees of freedom and a scale matrix given by:

$$T_n = T_0 + S_n$$

where S_n is the sample variance-covariance matrix. This result can be used for quantitative learning on the unknown parameters, for a given graphical structure. In addition, Dawid and Lauritzen (1993) show that the proposed prior distribution can be used to integrate the likelihood with respect to the unknown random parameters, obtaining the so-called marginal likelihood of a graph, which will be the main metric for structural learning. Such marginal likelihood is equal to:

$$P\left(x|G\right)=\frac{\prod_{c\in\mathcal{C}}p(x_C)}{\prod_{s\in\mathcal{S}}p(x_S)}$$

in which

$$p\left(x_C\right)=\left(2\pi\right)^{-\frac{n*|C|}{2}}\frac{k\left(|C|,\alpha+n\right)}{k\left(|C|,\alpha\right)}\frac{\det\left(T_0\right)^{\alpha/2}}{\det\left(T_n\right)^{(\alpha+n)/2}}$$

where $k(\cdot)$ is the multivariate gamma function, given by:

$$k_p\left(a\right)=\pi^{\frac{p(p-1)}{4}}\prod_{j=1}^{p}\Gamma\left(a+\frac{1-j}{2}\right)$$

Assume that we have several possible graphs, say $|G|$, and that they are equally likely a priory so that the probability of $|G|$ is:

$$P(G)=\frac{1}{|G|}$$

By Bayes rule, the posterior probability of a graph is given by:

$$P\left(G|x\right)\propto P\left(x|G\right)P\left(G\right)$$

and, therefore, since we assume a uniform prior over the graph structures, maximizing the posterior probability is equivalent to maximizing the marginal likelihood. For graphical model selection purposes we shall thus search in the space of all possible graphs for the structure such that:

$$G^*=\arg\max_G P\left(G|x\right)\propto\arg\max_G P\left(x|G\right)$$

A Bayesian model averaging approach does not force conditioning inferences on the (best) model chosen. If we assume that the network structure G is random, and assign a prior distribution on it, we can derive any inference on unknown parameters as model averages with respect to all possible graphical structures, with weights that correspond to the posterior probabilities of each network. This derives from the application of Bayes' Theorem, as follows:

$$P(\Sigma|X)=P(\Sigma|x,G)P(G|x)$$

Note that, in many real problems, the number of possible graphical structures could be very large and we may need to restrict the number of models to be averaged. This can be done efficiently, for example, following a simulation-based procedure for model search, such as Markov Chain Monte Carlo (MCMC) sampling. In our context, given an initial graph, the algorithm samples a new graph using a proposal distribution. To guarantee irreducibility of the Markov chain, we follow Giudici and Spelta (2016) to test whether the proposed graph is decomposable. The newly sampled graph is then compared with the old graph, calculating the ratio between the two marginal likelihoods, if the ratio is greater than a predetermined threshold (acceptance probability), the proposal is accepted, otherwise it is rejected. The algorithm continues until practical convergence is reached.

By using NetMES within the previously described Bayesian graphical model, we average NetMES as follows:

$$E(MES|x) = \sum_{g} E(MES|x, g)P(g|x), \tag{6}$$

where x represents the observed data evidence and g a specific network model. The estimated $E(MES|X)$ is referred to as a Bayesian Network based Marginal Expected Shortfall measure (Bayesian NetMES).

4.4 MES, NetMES and Bayesian NetMES Empirical Findings

We use MES, NetMES and Bayesian NetMES to capture the vulnerability of the financial institution to a market wide systemic shock. The systemic risk of the large/small-cap institutions using the proposed risk measures are presented in a descending order for the top six ranking institutions, from the highest to the lowest risk level. To take into consideration the presence of the 2007-2008 financial crisis within our study time line (2005-2014), we present the top six ranking institution per sub-industry every two years, the resulting sub-periods cover the pre-crisis (2005-2006), the crisis (2007-2008), and the post-crisis periods of 2009-2010, 2011-2012 and 2013-2014. For each sub-period, the institutions and the countries that they belong to are provided in a dot joint ticker country column (Ticker.Country). The provided specifications are applied on each sub-industry included in the given index.

We start with the large index systemic risk results. The Large index top six ranking institutions per sub-industry are provided in Tables 3, 4 and 5 for MES, NetMES and Bayesian NetMES, respectively. The large index financial institutions are classified into six groups according to the financial institution specialization, the sub-industries and the number of institutions per industry are: 39 Asset Management & Custody Ban (AMC), 131 Diversified Banks (DB), 8 Diversified Capital Markets (DCM), 19 Investment Banking & Brokerage (IBB), 98 Regional Banks (RB), and 11 Thrifts & Mortgage Finance (TMF).

Tables 3, 4 and 5 about here

We summaries the large index sub-industry systemic risk results, from the three previous tables, in Table 9. This Table provides the estimation of the large index two-years, and overall averages, for the systemic risk indicators of the top six institutions per sub-industry. Panel A, B and C provide the average per sub-industry of top six MES, top six NetMES, and top six Bayesian NetMES, respectively.

Table 9 about here

In Table 9, all three panels: A, B, and C, show that the large index sub-industry that has the highest overall average, across all periods, for top six MES, NetMES and Bayesian NetMES is Diversified Banks (DB), followed by Asset Management & Custody Ban (AMC), and by Investment Banking & Brokerage (IBB). Furthermore, the crisis two-year period show the same MES and NetMES ranking order, but the Bayesian NetMES shows that the higher average sub-industry is Asset Management & Custody Ban (AMC), followed by Diversified Banks (DB) and by Thrifts & Mortgage Finance (TMF).

The change magnitude of the systemic risk indicators during the crisis period reveal another aspect of the sub-industries risk level. MES shows that Diversified Banks (DB) experienced the highest increase of 41 percent during the crisis period (2007-2008), followed by 35 percent for Thrifts & Mortgage Finance (TMF). While NetMES and Bayesian NetMES show that Thrifts & Mortgage Finance (TMF) is the one that has the highest increase of 53 percent and 0.11 percent, respectively, followed by 24 percent and 0.03 percent for Diversified Banks (DB). The sub-industries systemic risk change magnitude can be interpreted in relation to the level of the financial leverage ratio that is provided in Table 11 [3].

Table 11 about here

Panel A in Table 11, for large index sub-industries, show that Thrifts & Mortgage Finance (TMF) is the one that has the highest leverage increase of 14.9 percent during the crisis period, followed by 0.95 percent for Diversified Banks (DB). It is noticeable that change magnitude of NetMES and Bayesian NetMES is affected by the change magnitude of leverage. This indicates that the change magnitude within the netted financial risk network is leverage driven, which captures the specificity of the subprime mortgage crisis. This feature infuse the debate on MES rational concept, in which MES is argued to be close to the Too Interconnected To Fail logic (TIF), rather than Too Big to Fail one (TBTF) (see e.g. Banulescu and Dumitrescu 2015). This logical relation can also be noticed from the sub-industries market capitalization total amounts, that are provided in Table 12 in billion dollars.

Table 12 about here

Panel A in Table 12, for large index sub-industries, show that Diversified Banks (DB) has the highest total market capitalization for the overall and the crisis periods, and the highest change in magnitude with an increase of 1.67 percent during the crisis period, while the change is a decrease of 1.32 percent for Thrifts & Mortgage Finance (TMF), consistently with its higher leverage increase relative to its smaller capitalization.

Next, we report the systemic risk vulnerability level of the small index institutional participants. The Small index top six ranking institutions per sub-industry are provided in Tables 6, 7 and 8 for MES, NetMES and Bayesian NetMES, respectively. The small index financial institutions are classified into five groups according to the financial institution specialization, the sub-industries and the number of institutions per industry are: 23 Asset Management & Custody Ban (AMC), 18 Diversified Banks (DB), 32 Investment Banking & Brokerage (IBB), 87 Regional Banks (RB), and 14 Thrifts & Mortgage Finance (TMF). Unlike the large index, Diversified Capital Markets (DCM) are omitted due to missing observations.

Tables 6, 7 and 8 about here

[3] We estimate financial leverage as the ratio of short and long term debt + market capitalization, divided by market capitalization.

We summaries the small index sub-industry results from the three tables in Table 10. This Table provides the estimation of the small index two-years and overall average, for the systemic risk indicators of the top six institutions per sub-industry. Panel A, B and C provide the average per sub-industry of top six MES, top six NetMES, and top six Bayesian NetMES, respectively.

Table 10 about here

In Table 10, the three panels: A, B, and C show that the small index sub-industry that has the highest top six average MES is Regional Banks (RB). Asset Management & Custody Ban (AMC) is the second highest based on MES, but Thrifts & Mortgage Finance (TMF) is the second highest based on NetMES and Bayesian NetMES. The same rankings for the three panels are sustained during the crisis period. Furthermore, the highest magnitude change in MES during crisis period is an increase of 1.39 percent for Thrifts & Mortgage Finance (TMF), 1.36 percent for Regional Banks (RB), and 0.97 percent for Asset Management & Custody Ban (AMC). NetMES and Bayesian Net MES show the same rankings, nevertheless, they show that the difference in the magnitude change for Thrifts & Mortgage Finance (TMF) is almost twice that of Regional Banks (RB), rather than a merely negligible change as in the case of MES.

Panel B in Table 11, for small index sub-industries, show that Thrifts & Mortgage Finance (TMF) is the one that has the highest leverage increase of 22.56 percent during the crisis period, followed by 0.52 percent for Regional Banks (RB). As in the large index case, the change magnitude of NetMES and Bayesian NetMES is affected by the change magnitude of leverage. Likewise, Panel B in Table 12, for small index sub-industries, show that Regional Banks (RB) has the highest total market capitalization for the overall and the crisis periods. However, the only two sub-industries that show a decrease during crisis period in their market capitalization share are: Regional Banks (RB)sub-industry with a decrease of 8.9 percent, followed by 3 percent decrease for Thrifts & Mortgage Finance (TMF), showing a similar relation to leverage as in large index.

5 Conclusions

In this work, we investigate if the lead-lag relation that we found from large to small-cap returns manifests itself not only at the aggregate index return level, but also at the individual volatity level, using systemic risk indicators. In other words, we test whether a large-cap companies lead-lags small-cap ones, not only in terms of returns, as in the previous sections, but also in terms of risk. To estimate the risk exposure of an individual institutions to the market, we use the standard bivariate based marginal expected shortfall (MES) systemic risk measure, as well as two alternatives: the network based MES (NetMES) that extends MES taking multivariate dependences into account; and the Bayesian NetMES, that further accounts for network model uncertainty. Upon the estimation of the MES, NetMES and Bayesian NetMES, we rank institutions based on the systemic risk indicators in a descending order, from highest to lowest systemic risk level.

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Table 1: Descriptive statistics for the large and small capitalization index returns (LCR and SCR, respectively). The sample spans weekly the period 01/01/2005 - 12/31/2014. .

	Mean	Median	Maximum	Minimum	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
LCR	0.0011	0.0036	0.1360	-0.1778	0.0295	-0.6658	8.7550	757.4852	0.0000
SCR	0.0014	0.0033	0.0825	-0.1367	0.0187	-1.3378	11.9019	1872.08	0.0000

Table 2: Vector Autoregressive Estimates.

	1/18/2005-12/26/2006		1/18/2007-12/26/2008		1/18/2009-12/26/2010		1/18/2011-12/26/2012		1/18/2013-12/26/2014	
	LCR_t	SCR_t	LCR_t	SCR_t	LCR_t	SCR_t	LCR_t	SCR_t	LCR_t	SCR_t
LCR_{t-1}	-0.033174	0.030592	-0.077557	0.052010	-0.080970	0.041818	-0.200794	0.114230	-0.027921	-0.133729
	(0.06815)	(0.07671)	(0.06348)	(0.06244)	(0.05866)	(0.06644)	(0.07874)	(0.05269)	(0.08220)	(0.04914)
	[-0.48678]	[0.39882]	[-1.22166]	[0.83295]	[-1.38044]	[0.62944]	[-2.55005]	[2.16780]	[-0.33967]	[-2.72132]
SCR_{t-1}	0.958834	0.044735	1.231640	0.035198	1.222926	0.203633	1.114327	0.095961	1.139503	0.290934
	(0.08913)	(0.10032)	(0.10229)	(0.10061)	(0.08712)	(0.09868)	(0.14549)	(0.09736)	(0.15372)	(0.09190)
	[10.7579]	[0.44593]	[12.0405]	[0.34985]	[14.0375]	[2.06366]	[7.65935]	[0.98564]	[7.41303]	[3.16592]
C	4.24E-05	0.003774	-0.001035	-0.003459	-0.000505	0.003208	0.000347	7.03E-05	-0.000577	0.001986
	(0.00105)	(0.00118)	(0.00256)	(0.00252)	(0.00220)	(0.00249)	(0.00232)	(0.00155)	(0.00137)	(0.00082)
	[0.04030]	[3.18883]	[-0.40476]	[-1.37531]	[-0.22965]	[1.28862]	[0.14945]	[0.04527]	[-0.42197]	[2.42872]
R^2	0.539953	0.003539	0.595804	0.007692	0.664488	0.051497	0.387368	0.055899	0.359637	0.127920
$\bar{R}^2$	0.530659	-0.016591	0.587800	-0.011958	0.657844	0.032714	0.375115	0.037017	0.346830	0.110478

Table 3: MES of Large Institutions.

This table provides the top six MES rankings of the large index financial institutions, classified into six groups according to the financial institution specialization, which are: Asset Management & Custody Ban (AMC), Diversified Capital Markets (DCM), Diversified Banks (DB), Investment Banking & Brokerage (IBB), Regional Banks (RB), and Thrifts & Mortgage Finance (TMF). The MES is averaged over a two year sub-period from the beginning of January 2005 until the end of December 2014 as provided in columns 2,4,6,8 and 10. The Ticker.Country in columns 1,3,5 and 7 provide the code of the specified institution and its country code.

Sub-Industry Type: Asset Management & Custody Ban (AMC)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
LM.US	1.424	LM.US	2.006	LM.US	2.265	8595.JP	1.456	8595.JP	1.290
8595.JP	1.148	8595.JP	1.661	8595.JP	1.702	LM.US	1.420	LM.US	1.153
SANTGRU.CI	1.022	VPBN.SW	1.237	VPBN.SW	1.649	SANTGRU.CI	1.011	SANTGRU.CI	0.956
MLP.GR	0.951	MLP.GR	1.093	MLP.GR	1.147	VONN.SW	0.995	MLP.GR	0.833
VPBN.SW	0.836	SANTGRU.CI	1.089	SANTGRU.CI	1.121	MLP.GR	0.933	VPBN.SW	0.810
VONN.SW	0.779	VONN.SW	1.088	VONN.SW	1.072	VPBN.SW	0.906	VONN.SW	0.749
Sub-Industry Type: Diversified Capital Markets (DCM)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
BAC.US	1.892	BAC.US	2.610	HB.CY	4.167	ALPHA.GA	4.882	BAC.US	4.562
ALBK.ID	1.502	HB.CY	1.901	BAC.US	3.193	BAC.US	4.149	TPEIR.GA	3.683
SCOTIAC1.PE	1.404	TPEIR.GA	1.726	ALPHA.GA	2.957	TPEIR.GA	3.872	ALPHA.GA	3.068
CHIB.PM	1.369	ALPHA.GA	1.702	BAP.US	2.597	MB.IM	1.861	AHB.MK	2.047
ALPHA.GA	1.366	BAP.US	1.681	TPEIR.GA	2.411	AHB.MK	1.797	BCE.MC	1.652
TMB.TB	1.273	ALBK.ID	1.665	SWEDA.SS	2.011	BCE.MC	1.678	MB.IM	1.590
Sub-Industry Type: Diversified Capital Markets (DCM)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
KN.FP	0.254	KN.FP	0.468	KN.FP	0.779	KN.FP	0.495	KN.FP	0.324
165.HK	0.169	165.HK	0.371	165.HK	0.653	165.HK	0.350	165.HK	0.214
INL.SJ	0.157	INL.SJ	0.211	INL.SJ	0.233	INL.SJ	0.160	INL.SJ	0.138
MQG.AU	0.067	MQG.AU	0.115	MQG.AU	0.115	MQG.AU	0.082	MQG.AU	0.064
6800.KS	0.018	6800.KS	0.039	DBK.GR	0.073	6800.KS	0.030	6800.KS	0.024
DBK.GR	0.014	DBK.GR	0.037	6800.KS	0.037	DBK.GR	0.020	DBK.GR	0.014
Sub-Industry Type: Investment Banking & Brokerage (IBB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
8616.JP	1.888	8616.JP	2.058	8616.JP	1.895	8616.JP	2.161	8616.JP	3.637
GS.US	1.098	GS.US	1.350	GS.US	1.314	GS.US	1.015	GS.US	1.096
AMTD.US	0.519	8601.JP	0.858	8601.JP	0.790	8601.JP	0.742	8601.JP	0.625
ITG.US	0.490	AMTD.US	0.683	AMTD.US	0.614	AMTD.US	0.587	AMTD.US	0.549
8601.JP	0.476	ITG.US	0.563	ITG.US	0.604	6005.TT	0.548	ITG.US	0.473
6005.TT	0.369	6005.TT	0.522	6005.TT	0.508	ITG.US	0.513	6005.TT	0.329
Sub-Industry Type: Regional Banks (RB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
CAF.FP	0.931	CAF.FP	1.271	CAF.FP	1.379	CAF.FP	1.301	CAF.FP	0.967
CRAP.FP	0.451	CRAP.FP	0.639	CRAP.FP	0.794	CRAP.FP	0.660	CRAP.FP	0.504
OLB.GR	0.318	OLB.GR	0.416	OLB.GR	0.366	OLB.GR	0.435	OLB.GR	0.440
626.HK	0.536	626.HK	0.819	626.HK	0.894	626.HK	0.617	626.HK	0.435
8324.JP	-1.359	8324.JP	-1.441	8324.JP	-1.356	8324.JP	-1.390	8324.JP	-1.419
8327.JP	-0.689	8327.JP	-0.705	8327.JP	-0.645	8327.JP	-0.553	8327.JP	-0.610
Sub-Industry Type: Thrifts & Mortgage Finance (TMF)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
PAG.LN	0.933	PAG.LN	2.252	PAG.LN	1.650	PAG.LN	0.997	PAG.LN	0.879
AF.US	0.297	AF.US	0.532	AF.US	0.760	AF.US	0.510	AF.US	0.331
CFFN.US	0.217	CFFN.US	0.421	MTG.US	0.464	MTG.US	0.339	CFFN.US	0.192
MTG.US	0.093	MTG.US	0.348	CFFN.US	0.433	CFFN.US	0.241	MTG.US	0.191
TRST.US	0.056	TRST.US	0.093	TRST.US	0.109	TRST.US	0.075	TRST.US	0.065
NYCB.US	0.038	NYCB.US	0.075	NYCB.US	0.078	NYCB.US	0.053	NYCB.US	0.040

Table 4: NetMES of Large Institutions.

This table provides the top six NetMES rankings of the large index financial institutions, classified into six groups according to the financial institution specialization, which are: Asset Management & Custody Ban (AMC), Diversified Capital Markets (DCM), Diversified Banks (DB), Investment Banking & Brokerage (IBB), Regional Banks (RB), and Thrifts & Mortgage Finance (TMF). The NetMES is averaged over a two year sub-period from the beginning of January 2005 until the end of December 2014 as provided in columns 2,4,6,8 and 10. The Ticker.Country in columns 1,3,5 and 7 provide the code of the specified institution and its country code.

Sub-Industry Type: Asset Management & Custody Ban (AMC)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
8595.JP	1.592	8595.JP	1.835	8595.JP	1.912	8595.JP	1.707	8595.JP	1.727
LM.US	1.567	VONN.SW	1.727	VONN.SW	1.676	VONN.SW	1.646	VONN.SW	1.450
VONN.SW	1.388	LM.US	1.650	LM.US	1.625	LM.US	1.242	LM.US	1.127
SANTGRU.CI	0.997	SANTGRU.CI	1.011	VPBN.SW	1.092	SANTGRU.CI	1.011	SANTGRU.CI	1.011
ADN.LN	0.796	VPBN.SW	0.967	SANTGRU.CI	1.011	ADN.LN	0.788	ADN.LN	0.796
FII.US	0.767	RAT.LN	0.844	RAT.LN	0.801	FII.US	0.755	FII.US	0.739
Sub-Industry Type: Diversified Banks (DB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
HB.CY	1.650	HB.CY	2.020	HB.CY	3.225	ALPHA.GA	2.779	ALPHA.GA	2.426
RHBC.MK	1.613	BNII.IJ	1.925	BNII.IJ	2.551	CIMB.MK	2.023	BNII.IJ	1.884
BNII.IJ	1.604	RHBC.MK	1.672	CIMB.MK	2.089	BNII.IJ	1.979	HB.CY	1.728
ALBK.ID	1.376	BC.SW	1.601	BC.SW	1.846	HB.CY	1.829	CIMB.MK	1.631
ALPHA.GA	1.364	ALPHA.GA	1.600	ALPHA.GA	1.623	KBC.BB	1.558	RHBC.MK	1.471
CIMB.MK	1.282	CIMB.MK	1.532	BAP.US	1.612	RHBC.MK	1.533	ALBK.ID	1.436
Sub-Industry Type: Diversified Capital Markets (DCM)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
DBK.GR	0.544	DBK.GR	0.941	DBK.GR	1.950	DBK.GR	0.695	DBK.GR	0.510
165.HK	0.383	INL.SJ	0.495	165.HK	1.040	165.HK	0.521	165.HK	0.378
INL.SJ	0.382	165.HK	0.492	KN.FP	0.556	INL.SJ	0.351	INL.SJ	0.339
KN.FP	0.251	KN.FP	0.378	INL.SJ	0.484	KN.FP	0.345	KN.FP	0.266
6800.KS	0.033	6800.KS	0.046	6800.KS	0.048	6800.KS	0.042	6800.KS	0.036
MQG.AU	-0.042	MQG.AU	-0.062	MQG.AU	-0.059	MQG.AU	-0.043	MQG.AU	-0.037
Sub-Industry Type: Investment Banking & Brokerage (IBB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
8616.JP	2.498	8616.JP	2.471	8616.JP	2.142	8616.JP	2.606	8616.JP	4.213
GS.US	1.606	GS.US	1.643	GS.US	1.566	GS.US	1.417	GS.US	1.518
BGCP.US	0.562	BGCP.US	0.650	BGCP.US	0.993	BGCP.US	0.577	BGCP.US	0.566
AMTD.US	0.411	8601.JP	0.609	3450.KS	0.646	8601.JP	0.521	8601.JP	0.517
8601.JP	0.403	8613.JP	0.436	8601.JP	0.576	AMTD.US	0.409	AMTD.US	0.410
8613.JP	0.290	AMTD.US	0.419	8613.JP	0.434	8613.JP	0.318	8613.JP	0.275
Sub-Industry Type: Regional Banks (RB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
8543.JP	1.394	CAF.FP	0.600	CAF.FP	0.594	CAF.FP	0.599	CAF.FP	0.582
BPOP.US	0.959	CRAP.FP	0.056	CRAP.FP	0.060	CRAP.FP	0.055	CRAP.FP	0.051
FMBI.US	0.850	OLB.GR	0.303	OLB.GR	0.326	OLB.GR	0.399	OLB.GR	0.432
SNV.US	0.845	626.HK	-0.111	626.HK	-0.111	626.HK	-0.104	626.HK	-0.091
UMBF.US	0.772	8324.JP	-0.312	8324.JP	-0.312	8324.JP	-0.312	8324.JP	-0.312
SRCE.US	0.769	8327.JP	-0.564	8327.JP	-0.545	8327.JP	-0.537	8327.JP	-0.558
Sub-Industry Type: Thrifts & Mortgage Finance (TMF)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
FMCC.US	2.017	FMCC.US	3.830	FMCC.US	2.869	FMCC.US	2.201	FMCC.US	1.933
PAG.LN	0.905	PAG.LN	1.955	PAG.LN	1.375	PAG.LN	0.947	PAG.LN	0.937
CFFN.US	0.370	CFFN.US	0.550	CFFN.US	0.627	CFFN.US	0.381	CFFN.US	0.318
MTG.US	0.061	MTG.US	0.165	MTG.US	0.207	MTG.US	0.170	MTG.US	0.106
NYCB.US	0.047	NYCB.US	0.070	NYCB.US	0.087	NYCB.US	0.055	NYCB.US	0.044
TRST.US	0.039	TRST.US	0.056	TRST.US	0.065	TRST.US	0.046	TRST.US	0.042

Table 5: Bayesian NetMES of Large Institutions.

This table provides the top six Bayesian NetMES rankings of the large index financial institutions, classified into six groups according to the financial institution specialization, which are: Asset Management & Custody Ban (AMC), Diversified Capital Markets (DCM), Diversified Banks (DB), Investment Banking & Brokerage (IBB), Regional Banks (RB), and Thrifts & Mortgage Finance (TMF). The Bayesian NetMES is averaged over a two year sub-period from the beginning of January 2005 until the end of December 2014 as provided in columns 2,4,6,8 and 10. The Ticker.Country in columns 1,3,5 and 7 provide the code of the specified institution and its country code.

Sub-Industry Type: Asset Management & Custody Ban (AMC)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
LM.US	0.0030637	VONN.SW	0.0034603	8595.JP	0.0034986	VONN.SW	0.0032989	8595.JP	0.0031603
8595.JP	0.0029129	8595.JP	0.0033585	VONN.SW	0.0033581	8595.JP	0.0031228	VONN.SW	0.0029065
VONN.SW	0.0027821	LM.US	0.0032272	LM.US	0.0031771	LM.US	0.0024283	LM.US	0.0022033
SANTGRU.CI	0.0019142	SANTGRU.CI	0.0019400	SANTGRU.CI	0.0019400	SANTGRU.CI	0.0019400	SANTGRU.CI	0.0019400
FII.US	0.0015568	RAT.LN	0.0018339	RAT.LN	0.0017412	RAT.LN	0.0015411	FII.US	0.0015008
RAT.LN	0.0015489	VPBN.SW	0.0014835	VPBN.SW	0.0016758	FII.US	0.0015318	RAT.LN	0.0014924
Sub-Industry Type: Diversified Banks (DB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
CHIB.PM	0.0024254	CHIB.PM	0.0025962	HB.CY	0.0039188	ALPHA.GA	0.0042210	ALPHA.GA	0.0036849
ALPHA.GA	0.0020716	HB.CY	0.0024561	BNII.IJ	0.0029301	CHIB.PM	0.0024621	CHIB.PM	0.0024973
BAP.US	0.0020073	ALPHA.GA	0.0024296	BAP.US	0.0029105	BNII.IJ	0.0022737	BAP.US	0.0022348
HB.CY	0.0020061	BC.SW	0.0022385	SWEDA.SS	0.0025943	BAP.US	0.0022522	BNII.IJ	0.0021641
SBIN.IN	0.0020040	BNII.IJ	0.0022114	BC.SW	0.0025816	HB.CY	0.0022228	HB.CY	0.0020995
RHBC.MK	0.0019733	BAP.US	0.0021825	CHIB.PM	0.0025414	CIMB.MK	0.0021323	SBIN.IN	0.0020129
Sub-Industry Type: Diversified Capital Markets (DCM)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
DBK.GR	0.0011810	DBK.GR	0.0020445	DBK.GR	0.0042380	DBK.GR	0.0015111	DBK.GR	0.0011094
INL.SJ	0.0008685	INL.SJ	0.0011257	165.HK	0.0022166	165.HK	0.0011096	165.HK	0.0008046
165.HK	0.0008158	165.HK	0.0010467	INL.SJ	0.0010990	INL.SJ	0.0007972	INL.SJ	0.0007707
KN.FP	0.0004886	KN.FP	0.0007361	KN.FP	0.0010826	KN.FP	0.0006714	KN.FP	0.0005172
6800.KS	0.0000303	6800.KS	0.0000424	6800.KS	0.0000442	6800.KS	0.0000387	6800.KS	0.0000333
MQG.AU	-0.0000880	MQG.AU	-0.0001286	MQG.AU	-0.0001230	MQG.AU	-0.0000880	MQG.AU	-0.0000766
Sub-Industry Type: Investment Banking & Brokerage (IBB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
8616.JP	0.0051125	8616.JP	0.0050580	8616.JP	0.0043830	8616.JP	0.0053347	8616.JP	0.0086220
GS.US	0.0033508	GS.US	0.0034266	GS.US	0.0032648	GS.US	0.0029560	GS.US	0.0031661
BGCP.US	0.0011521	BGCP.US	0.0013308	BGCP.US	0.0020348	BGCP.US	0.0011819	BGCP.US	0.0011601
AMTD.US	0.0008326	8601.JP	0.0012446	3450.KS	0.0012961	8601.JP	0.0010632	8601.JP	0.0010562
8601.JP	0.0008240	8613.JP	0.0009770	8601.JP	0.0011760	AMTD.US	0.0008296	AMTD.US	0.0008310
8613.JP	0.0006500	AMTD.US	0.0008487	8613.JP	0.0009731	8613.JP	0.0007134	8613.JP	0.0006167
Sub-Industry Type: Regional Banks (RB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
8543.JP	0.0022609	8543.JP	0.0022542	BPOP.US	0.0035117	BPOP.US	0.0024514	8543.JP	0.0021047
BPOP.US	0.0017738	BPOP.US	0.0022427	FMBI.US	0.0027937	8543.JP	0.0021647	BPOP.US	0.0019478
FMBI.US	0.0015365	FMBI.US	0.0017817	SNV.US	0.0025363	FMBI.US	0.0021179	FMBI.US	0.0016067
UMBF.US	0.0014879	UMBF.US	0.0017653	8543.JP	0.0021939	SNV.US	0.0020900	UMBF.US	0.0015610
SRCE.US	0.0014718	SNV.US	0.0016968	BBT.US	0.0019463	UMBF.US	0.0016000	SNV.US	0.0015111
CAF.FP	0.0012886	SRCE.US	0.0015843	UMBF.US	0.0015899	BBT.US	0.0015188	SRCE.US	0.0013875
Sub-Industry Type: Thrifts & Mortgage Finance (TMF)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
FMCC.US	0.0042236	FMCC.US	0.0080199	FMCC.US	0.0060056	FMCC.US	0.0046078	FMCC.US	0.0040478
PAG.LN	0.0018081	PAG.LN	0.0039047	PAG.LN	0.0027458	PAG.LN	0.0018921	PAG.LN	0.0018709
CFFN.US	0.0007462	CFFN.US	0.0011087	CFFN.US	0.0012633	CFFN.US	0.0007681	CFFN.US	0.0006419
MTG.US	0.0001432	MTG.US	0.0003873	MTG.US	0.0004870	MTG.US	0.0003997	MTG.US	0.0002504
NYCB.US	0.0001268	NYCB.US	0.0001895	NYCB.US	0.0002366	NYCB.US	0.0001484	NYCB.US	0.0001205
TRST.US	0.0000700	TRST.US	0.0001021	TRST.US	0.0001176	TRST.US	0.0000837	TRST.US	0.0000764

Table 6: MES of Small Institutions.

This table provides the top six MES rankings of the small index financial institutions, classified into five groups according to the financial institution specialization, which are: Asset Management & Custody Ban (AMC), Diversified Banks (DB), Investment Banking & Brokerage (IBB), Regional Banks (RB), and Thrifts & Mortgage Finance (TMF). The MES is averaged over a two year sub-period from the beginning of January 2005 until the end of December 2014 as provided in columns 2,4,6,8 and 10. The Ticker.Country in columns 1,3,5 and 7 provide the code of the specified institution and its country code.

Sub-Industry Type: Asset Management & Custody Ban (AMC)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
turn.US	3.480	DBAN.GR	4.472	DBAN.GR	4.090	turn.US	3.523	turn.US	3.266
PGR.SJ	2.959	666.HK	3.854	KA.NA	3.817	666.HK	3.200	EFS.GR	2.844
EFS.GR	2.952	turn.US	3.728	turn.US	3.582	DBAN.GR	3.077	PGR.SJ	2.545
DBAN.GR	2.696	KA.NA	3.673	PGR.SJ	3.408	EFS.GR	2.932	378.HK	2.485
666.HK	2.280	PGR.SJ	3.424	666.HK	3.400	PGR.SJ	2.604	666.HK	2.414
378.HK	2.225	EFS.GR	3.284	AIRE.SW	3.349	NORVE.FH	2.474	DBAN.GR	2.312
Sub-Industry Type: Diversified Banks (DB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
GSDHO.TI	4.776	GSDHO.TI	5.193	GSDHO.TI	4.329	GSDHO.TI	4.077	GSDHO.TI	4.669
BOS.PW	2.507	BOS.PW	2.836	BOS.PW	2.689	BOS.PW	2.635	BOS.PW	2.480
ALBAV.FH	2.192	ALBAV.FH	2.165	SPOG.NO	2.350	ALBAV.FH	2.383	ALBAV.FH	2.170
BCBB.BG	1.663	SVEG.NO	2.076	SVEG.NO	2.220	SVEG.NO	1.704	SVEG.NO	1.701
SVEG.NO	1.560	SPOG.NO	1.729	ALBAV.FH	2.194	SPOG.NO	1.484	BCBB.BG	1.452
SPOG.NO	1.320	BCBB.BG	1.702	BCBB.BG	1.514	BCBB.BG	1.273	SPOG.NO	1.335
Sub-Industry Type: Investment Banking & Brokerage (IBB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
OPY.US	2.557	OPY.US	3.947	OPY.US	5.163	OPY.US	4.032	PRO.IM	3.401
PRO.IM	2.416	PRO.IM	3.226	PRO.IM	5.117	PRO.IM	3.017	OPY.US	2.777
ASP.TB	2.171	CAY.LN	2.353	8614.JP	2.383	8614.JP	2.208	8625.JP	2.556
CAY.LN	2.158	8614.JP	2.285	CAY.LN	2.357	CAY.LN	2.138	8614.JP	2.177
8614.JP	2.083	ASP.TB	2.197	CFT.SW	2.341	CFT.SW	2.116	CAY.LN	2.058
8625.JP	1.993	619.HK	1.997	8625.JP	2.210	8625.JP	1.993	ASP.TB	1.971
Sub-Industry Type: Regional Banks (RB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
BEES3.BZ	3.680	SBCF.US	6.163	SBCF.US	9.372	CACB.US	5.517	SNBC.US	3.779
FSBK.US	3.257	BEES3.BZ	5.064	CACB.US	7.251	SNBC.US	5.454	CACB.US	3.475
CACB.US	3.177	CACB.US	4.187	IBCP.US	6.986	FUNC.US	5.450	SBCF.US	3.188
8338.JP	3.171	FSBK.US	4.094	SNBC.US	6.627	COB.US	5.265	FNCB.US	3.001
SBCF.US	3.066	FCBC.US	4.026	HTBK.US	6.379	IBCP.US	5.250	PCBK.US	2.830
FCBC.US	3.010	IBCP.US	4.000	MSFG.US	5.386	SBCF.US	4.562	FISI.US	2.665
Sub-Industry Type: Thrifts & Mortgage Finance (TMF)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
NASB.US	2.420	AGM.US	5.192	AGM.US	4.973	NASB.US	3.496	NASB.US	2.436
LD.FP	2.125	NASB.US	4.963	NASB.US	4.887	BSF.US	2.546	OCFC.US	2.266
OCFC.US	1.950	OCFC.US	2.910	PROV.US	4.538	LD.FP	2.396	LD.FP	2.203
AGM.US	1.846	PROV.US	2.529	OCFC.US	4.026	OCFC.US	2.324	AGM.US	1.796
PROV.US	1.571	LD.FP	2.308	LD.FP	2.636	AGM.US	2.115	PROV.US	1.437
SCB.CN	1.296	BSF.US	1.618	BSF.US	2.543	HFBC.US	1.598	BSF.US	1.324

Table 7: NetMES of Small Institutions.

This table provides the top six NetMES rankings of the small index financial institutions, classified into five groups according to the financial institution specialization, which are: Asset Management & Custody Ban (AMC), Diversified Banks (DB), Investment Banking & Brokerage (IBB), Regional Banks (RB), and Thrifts & Mortgage Finance (TMF). The NetMES is averaged over a two year sub-period from the beginning of January 2005 until the end of December 2014 as provided in columns 2,4,6,8 and 10. The Ticker.Country in columns 1,3,5 and 7 provide the code of the specified institution and its country code.

Sub-Industry Type: Asset Management & Custody Ban (AMC)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
378.HK	2.009	378.HK	2.090	378.HK	2.088	378.HK	2.176	378.HK	2.217
EFS.GR	1.315	DBAN.GR	1.738	DBAN.GR	1.612	21080.KS	1.474	EFS.GR	1.211
DBAN.GR	1.189	21080.KS	1.569	21080.KS	1.310	DBAN.GR	1.290	21080.KS	1.151
21080.KS	1.155	EFS.GR	1.397	EFS.GR	1.251	EFS.GR	1.223	DBAN.GR	1.133
turn.US	1.107	turn.US	1.123	turn.US	1.106	turn.US	1.104	turn.US	1.094
SAHA.GR	0.557	SAHA.GR	0.631	SAHA.GR	0.648	SAHA.GR	0.551	SAHA.GR	0.656
Sub-Industry Type: Diversified Banks (DB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
GSDHO.TI	2.357	GSDHO.TI	2.347	GSDHO.TI	2.107	GSDHO.TI	2.041	GSDHO.TI	2.314
BOS.PW	1.246	BOS.PW	1.304	BOS.PW	1.267	BOS.PW	1.243	BOS.PW	1.239
ALBAV.FH	1.051	ALBAV.FH	1.023	ALBAV.FH	1.037	ALBAV.FH	1.133	ALBAV.FH	1.050
NBKE.EY	0.653	NBKE.EY	0.733	NBKE.EY	0.694	NBKE.EY	0.526	LASP.DC	0.541
BCBB.BG	0.563	BCBB.BG	0.576	SVEG.NO	0.561	LASP.DC	0.512	NBKE.EY	0.503
LASP.DC	0.502	SVEG.NO	0.489	LASP.DC	0.555	SVEG.NO	0.429	BCBB.BG	0.490
Sub-Industry Type: Investment Banking & Brokerage (IBB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
OPY.US	1.793	OPY.US	2.214	OPY.US	2.724	OPY.US	2.398	OPY.US	1.862
CAY.LN	1.196	8614.JP	1.463	8614.JP	1.515	CAY.LN	1.187	CAY.LN	1.181
BFV.GR	1.161	CAY.LN	1.229	CAY.LN	1.219	BFV.GR	1.152	BFV.GR	1.144
8614.JP	1.020	BFV.GR	1.147	BFV.GR	1.155	8614.JP	1.086	8614.JP	1.018
PRO.IM	0.670	PRO.IM	0.794	PRO.IM	1.104	PRO.IM	0.782	PRO.IM	0.896
ASP.TB	0.644	ASP.TB	0.638	ASP.TB	0.648	ASP.TB	0.644	ASP.TB	0.641
Sub-Industry Type: Regional Banks (RB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
BEES3.BZ	4.466	BEES3.BZ	4.432	FNCB.US	5.371	FNCB.US	5.849	FNCB.US	4.969
FNCB.US	3.629	FNCB.US	4.092	SBCF.US	4.371	COB.US	3.933	BEES3.BZ	3.168
GRLA.DC	2.381	GRLA.DC	3.302	BYLK.US	3.573	BEES3.BZ	3.619	GRLA.DC	2.919
SBCF.US	2.331	SBCF.US	3.296	BEES3.BZ	3.545	GRLA.DC	3.142	SBCF.US	2.376
CCBG.US	1.917	PGC.US	2.222	GRLA.DC	3.433	SBCF.US	2.913	CCBG.US	1.927
PGC.US	1.900	BMTC.US	2.130	COB.US	2.777	fusb.US	2.085	PGC.US	1.903
Sub-Industry Type: Thrifts & Mortgage Finance (TMF)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
SCB.CN	3.572	AGM.US	4.007	SCB.CN	3.798	SCB.CN	2.570	SCB.CN	2.635
AGM.US	1.770	SCB.CN	3.570	AGM.US	3.522	BSF.US	2.447	AGM.US	1.819
LD.FP	1.646	OCFC.US	2.260	OCFC.US	2.766	AGM.US	2.136	OCFC.US	1.766
OCFC.US	1.562	NASB.US	2.101	BSF.US	2.131	OCFC.US	1.734	LD.FP	1.644
NASB.US	1.127	LD.FP	1.655	NASB.US	2.016	LD.FP	1.664	NASB.US	1.177
BSF.US	0.783	BSF.US	1.157	PROV.US	1.950	NASB.US	1.643	BSF.US	1.157

Table 8: Bayesian NetMES of Small Institutions.

This table provides the top six Bayesian NetMES rankings of the small index financial institutions, classified into five groups according to the financial institution specialization, which are: Asset Management & Custody Ban (AMC), Diversified Banks (DB), Investment Banking & Brokerage (IBB), Regional Banks (RB), and Thrifts & Mortgage Finance (TMF). The Bayesian NetMES is averaged over a two year sub-period from the beginning of January 2005 until the end of December 2014 as provided in columns 2,4,6,8 and 10. The Ticker.Country in columns 1,3,5 and 7 provide the code of the specified institution and its country code.

Sub-Industry Type: Asset Management & Custody Ban (AMC)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
378.HK	0.003690	378.HK	0.003837	378.HK	0.003834	378.HK	0.003995	378.HK	0.004070
turn.US	0.002801	DBAN.GR	0.003407	DBAN.GR	0.003160	21080.KS	0.002799	turn.US	0.002768
EFS.GR	0.002344	21080.KS	0.002979	turn.US	0.002799	turn.US	0.002794	DBAN.GR	0.002221
DBAN.GR	0.002331	turn.US	0.002841	21080.KS	0.002489	DBAN.GR	0.002530	21080.KS	0.002185
21080.KS	0.002193	EFS.GR	0.002490	EFS.GR	0.002229	EFS.GR	0.002180	EFS.GR	0.002159
PGR.SJ	0.001417	PGR.SJ	0.001480	PGR.SJ	0.001524	PGR.SJ	0.001319	PGR.SJ	0.001358
Sub-Industry Type: Diversified Banks (DB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
GSDHO.TI	0.004711	GSDHO.TI	0.004692	GSDHO.TI	0.004211	GSDHO.TI	0.004080	GSDHO.TI	0.004625
BOS.PW	0.002502	BOS.PW	0.002620	BOS.PW	0.002545	BOS.PW	0.002496	BOS.PW	0.002489
ALBAV.FH	0.002074	ALBAV.FH	0.002020	ALBAV.FH	0.002047	ALBAV.FH	0.002237	ALBAV.FH	0.002075
NBKE.EY	0.001446	NBKE.EY	0.001622	NBKE.EY	0.001538	NBKE.EY	0.001165	NBKE.EY	0.001113
BCBB.BG	0.001136	BCBB.BG	0.001161	LASP.DC	0.001056	LASP.DC	0.000976	LASP.DC	0.001030
LASP.DC	0.000957	LASP.DC	0.000926	BCBB.BG	0.000983	BCBB.BG	0.000805	BCBB.BG	0.000989
Sub-Industry Type: Investment Banking & Brokerage (IBB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
OPY.US	0.003513	OPY.US	0.004337	OPY.US	0.005336	OPY.US	0.004699	OPY.US	0.003648
CAY.LN	0.002227	8614.JP	0.002858	8614.JP	0.002958	CAY.LN	0.002210	CAY.LN	0.002198
BFV.GR	0.002195	CAY.LN	0.002287	PRO.IM	0.002487	BFV.GR	0.002175	BFV.GR	0.002161
8614.JP	0.001992	BFV.GR	0.002168	CAY.LN	0.002270	8614.JP	0.002121	PRO.IM	0.002017
PRO.IM	0.001510	PRO.IM	0.001790	BFV.GR	0.002182	PRO.IM	0.001761	8614.JP	0.001987
KAF.MK	0.000973	KAF.MK	0.000973	KAF.MK	0.000984	KAF.MK	0.001003	KAF.MK	0.000959
Sub-Industry Type: Regional Banks (RB)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
BEES3.BZ	0.008049	BEES3.BZ	0.007988	FNCB.US	0.008316	FNCB.US	0.009056	FNCB.US	0.007693
FNCB.US	0.005618	FNCB.US	0.006336	SBCF.US	0.007374	BEES3.BZ	0.006521	BEES3.BZ	0.005710
SBCF.US	0.003933	SBCF.US	0.005559	BYLK.US	0.006616	SBCF.US	0.004913	SBCF.US	0.004009
CCBG.US	0.002389	BYLK.US	0.003169	BEES3.BZ	0.006389	FUNC.US	0.003631	CFFI.US	0.002852
CNAF.US	0.002209	CFFI.US	0.003088	CFFI.US	0.004255	BYLK.US	0.003431	BYLK.US	0.002792
PFBX.US	0.002138	GRLA.DC	0.002957	GRLA.DC	0.003073	CFFI.US	0.003063	GRLA.DC	0.002614
Sub-Industry Type: Thrifts & Mortgage Finance (TMF)									
Ticker.Country	2005-2006	Ticker.Country	2007-2008	Ticker.Country	2009-2010	Ticker.Country	2011-2012	Ticker.Country	2013-2014
SCB.CN	0.006732	AGM.US	0.007862	SCB.CN	0.007157	BSF.US	0.004872	SCB.CN	0.004966
AGM.US	0.003473	SCB.CN	0.006728	AGM.US	0.006912	SCB.CN	0.004844	AGM.US	0.003569
LD.FP	0.003100	OCFC.US	0.004427	OCFC.US	0.005419	AGM.US	0.004192	OCFC.US	0.003459
OCFC.US	0.003060	NASB.US	0.004185	BSF.US	0.004244	OCFC.US	0.003396	LD.FP	0.003096
NASB.US	0.002245	LD.FP	0.003117	NASB.US	0.004015	NASB.US	0.003273	NASB.US	0.002344
BSF.US	0.001558	BSF.US	0.002303	PROV.US	0.003975	LD.FP	0.003133	BSF.US	0.002304

Table 9: Average of Top Six MES, NetMES, and Bayesian NetMES Per Large Index Sub-Industry.

This table provides average per sub-industry of Large Index. Panel A provides the average per sub-industry of top six MES. Panel B provides the average per sub-industry of top six NetMES. Panel C provides the average per sub-industry of top six Bayesian NetMES. All MES, NetMES and Bayesian NetMES are averaged over a two year sub-period from the beginning of January 2005 until the end of December 2014. The large index financial institutions are classified into six groups according to the financial institution specialization, which are: Asset Management & Custody Ban (AMC), Diversified Capital Markets (DCM), Diversified Banks (DB), Investment Banking & Brokerage (IBB), Regional Banks (RB), and Thrifts & Mortgage Finance (TMF).

Panel A: Large index average per sub-industry for top six of MES							
Industry		Top Six Average Per Period					Top Six Average
Type	Ticker	2005-2006	2007-2008	2009-2010	2011-2012	2013-2014	Per Industry
Asset Management & Custody Ban	AMC	1.027	1.362	1.493	1.120	0.965	1.193
Diversified Banks	DB	1.468	1.881	2.889	3.040	2.767	2.409
Diversified Capital Markets	DCM	0.113	0.207	0.315	0.190	0.130	0.191
Investment Banking & Brokerage	IBB	0.807	1.006	0.954	0.928	1.118	0.962
Regional Banks	RB	0.031	0.166	0.239	0.178	0.053	0.133
Thrifts & Mortgage Finance	TMF	0.272	0.620	0.582	0.369	0.283	0.425
Panel B: Large index average per sub-industry for top six of NetMES							
Industry		Top Six Average Per Period					Top Six Average
Type	Ticker	2005-2006	2007-2008	2009-2010	2011-2012	2013-2014	Per Industry
Asset Management & Custody Ban	AMC	1.184	1.339	1.353	1.191	1.142	1.242
Diversified Banks	DB	1.482	1.725	2.158	1.950	1.763	1.815
Diversified Capital Markets	DCM	0.258	0.382	0.670	0.319	0.249	0.375
Investment Banking & Brokerage	IBB	0.962	1.038	1.059	0.975	1.250	1.057
Regional Banks	RB	0.931	-0.005	0.002	0.017	0.017	0.193
Thrifts & Mortgage Finance	TMF	0.573	1.104	0.871	0.633	0.564	0.749
Panel B: Large index average per sub-industry for top six Bayesian NetMES							
Industry		Top Six Average Per Period					Top Six Average
Type	Ticker	2005-2006	2007-2008	2009-2010	2011-2012	2013-2014	Per Industry
Asset Management & Custody Ban	AMC	0.002296	0.002551	0.002565	0.002310	0.002201	0.002385
Diversified Banks	DB	0.002081	0.002352	0.002913	0.002594	0.002449	0.002478
Diversified Capital Markets	DCM	0.000549	0.000811	0.001426	0.000673	0.000526	0.000797
Investment Banking & Brokerage	IBB	0.001987	0.002148	0.002188	0.002013	0.002575	0.002182
Regional Banks	RB	0.001637	0.001888	0.002429	0.001990	0.001686	0.001926
Thrifts & Mortgage Finance	TMF	0.001186	0.002285	0.001809	0.001317	0.001168	0.001553

Table 10: Average of Top Six MES, NetMES, and Bayesian NetMES Per Small Index Sub-Industry .

This table provides average per sub-industry of Small Index. Panel A provides the average per sub-industry of top six MES. Panel B provides the average per sub-industry of top six NetMES. Panel C provides the average per sub-industry of top six Bayesian NetMES. All MES, NetMES and Bayesian NetMES are averaged over a two year sub-period from the beginning of January 2005 until the end of December 2014. The small index financial institutions are classified into five groups according to the financial institution specialization, which are: Asset Management & Custody Ban (AMC), Diversified Banks (DB), Investment Banking & Brokerage (IBB), Regional Banks (RB), and Thrifts & Mortgage Finance (TMF).

Panel A: Small index average per sub-industry for top six of MES							
Industry		Top Six Average Per Period					Top Six Average
Type	Ticker	2005-2006	2007-2008	2009-2010	2011-2012	2013-2014	Per Industry
Asset Management & Custody Ban	AMC	2.765	3.739	3.608	2.968	2.644	3.145
Diversified Banks	DB	2.336	2.617	2.549	2.259	2.301	2.413
Investment Banking & Brokerage	IBB	2.230	2.668	3.262	2.584	2.490	2.647
Regional Banks	RB	3.227	4.589	7.000	5.250	3.156	4.644
Thrifts & Mortgage Finance	TMF	1.868	3.253	3.934	2.412	1.910	2.676
Panel B: Small index average per sub-industry for top six of NetMES							
Industry		Top Six Average Per Period					Top Six Average
Type	Ticker	2005-2006	2007-2008	2009-2010	2011-2012	2013-2014	Per Industry
Asset Management & Custody Ban	AMC	1.222	1.424	1.336	1.303	1.243	1.306
Diversified Banks	DB	1.062	1.079	1.037	0.981	1.023	1.036
Investment Banking & Brokerage	IBB	1.081	1.248	1.394	1.208	1.124	1.211
Regional Banks	RB	2.771	3.246	3.845	3.590	2.877	3.266
Thrifts & Mortgage Finance	TMF	1.743	2.458	2.697	2.032	1.700	2.126
Panel B: Small index average per sub-industry for top six Bayesian NetMES							
Industry		Top Six Average Per Period					Top Six Average
Type	Ticker	2005-2006	2007-2008	2009-2010	2011-2012	2013-2014	Per Industry
Asset Management & Custody Ban	AMC	0.002463	0.002839	0.002672	0.002603	0.002460	0.002607
Diversified Banks	DB	0.002138	0.002173	0.002063	0.001960	0.002054	0.002078
Investment Banking & Brokerage	IBB	0.002068	0.002402	0.002703	0.002328	0.002162	0.002333
Regional Banks	RB	0.004056	0.004849	0.006004	0.005102	0.004278	0.004858
Thrifts & Mortgage Finance	TMF	0.003361	0.004770	0.005287	0.003952	0.003290	0.004132

Table 11: Financial Leverage per Sub-Industry .

This Table provides the financial leverage per sub-industry. Panel A provides leverage of the large index financial institutions and Panel B provides leverage of the small index financial institution, both large and small institutions are classified into six sub-industry groups according to the financial institution specialization, calculated over a two year sub-period from the beginning of January 2005 until the end of December 2014.

Panel A: Large Index Leverage							
Industry		Average Per Period					Average
Type	Ticker	2005-2006	2007-2008	2009-2010	2011-2012	2013-2014	Per Industry
Asset Management & Custody Ban	AMC	1.44	1.82	1.77	1.49	1.41	1.58
Diversified Banks	DB	2.80	3.75	5.67	6.23	4.68	4.62
Diversified Capital Markets	DCM	2.65	3.77	3.76	4.04	4.24	3.69
Investment Banking & Brokerage	IBB	3.34	4.13	4.97	7.13	5.51	5.02
Regional Banks	RB	1.81	2.28	2.92	2.58	2.36	2.39
Thrifts & Mortgage Finance	TMF	5.75	20.64	144.54	382.19	82.07	127.04
Panel B: Small Index Leverage							
Industry		Average Per Period					Average
Type	Ticker	2005-2006	2007-2008	2009-2010	2011-2012	2013-2014	Per Industry
Asset Management & Custody Ban	AMC	2.16	2.43	2.61	1.78	1.60	2.12
Diversified Banks	DB	5.09	8.14	11.71	7.82	6.89	7.93
Investment Banking & Brokerage	IBB	1.48	1.78	1.78	3.13	4.02	2.44
Regional Banks	RB	1.78	2.31	3.54	2.99	2.23	2.57
Thrifts & Mortgage Finance	TMF	5.36	27.92	56.08	23.04	10.45	24.57

Table 12: Market Capitalization per Sub-Industry .

The table provides the market capitalization per sub-industry. Panel A provides market capitalization of the large index financial institutions and Panel B provides market capitalization of the small index financial institution, both large and small institutions are classified into six sub-industry groups according to the financial institution specialization, calculated over a two year sub-period from the beginning of January 2005 until the end of December 2014.

Panel A: Large Index Market Capitalization							
Industry		Total Per Period					Total
Type	Ticker	2005-2006	2007-2008	2009-2010	2011-2012	2013-2014	Per Industry
Asset Management & Custody Ban	AMC	212,536	271,262	197,192	219,003	289,875	1,189,869
Diversified Banks	DB	2,092,360	2,278,660	1,944,820	2,231,659	2,941,330	11,488,829
Diversified Capital Markets	DCM	88,566	109,625	77,923	77,553	95,089	448,757
Investment Banking & Brokerage	IBB	210,996	216,106	174,965	151,316	219,165	972,547
Regional Banks	RB	342,808	300,445	228,424	257,018	322,905	1,451,600
Thrifts & Mortgage Finance	TMF	125,271	90,002	36,084	37,321	67,174	355,852
Panel B: Small Index Market Capitalization							
Industry		Total Per Period					Total
Type	Ticker	2005-2006	2007-2008	2009-2010	2011-2012	2013-2014	Per Industry
Asset Management & Custody Ban	AMC	4,634	5,834	3,727	3,794	4,039	22,029
Diversified Banks	DB	4,034	6,734	6,180	5,345	5,331	27,623
Diversified Capital Markets	DCM	2,077	2,440	857	680	600	6,653
Investment Banking & Brokerage	IBB	5,857	7,802	6,015	5,250	5,904	30,827
Regional Banks	RB	19,721	17,564	11,918	13,117	16,876	79,195
Thrifts & Mortgage Finance	TMF	3,468	2,506	1,690	1,988	2,632	12,282

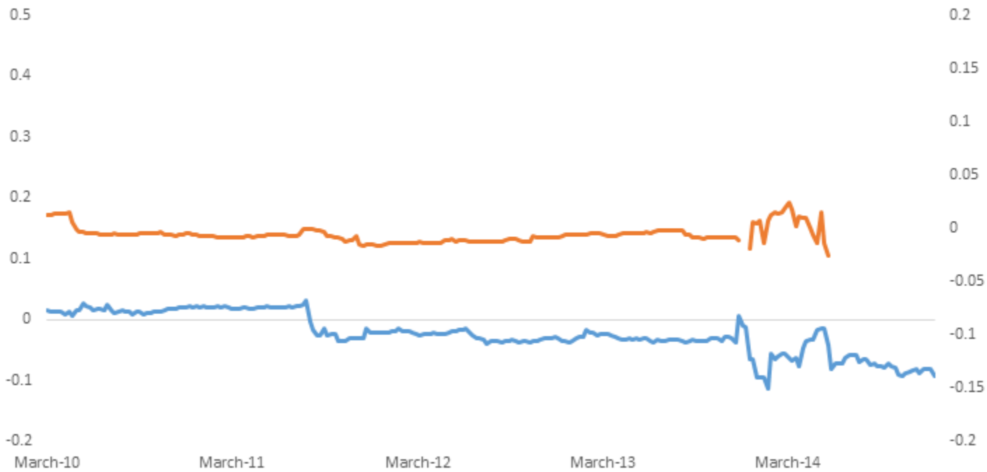


Figure 1: Autoregressive coefficient estimates ϕ_{11} and ϕ_{22} based on eq.(1). Orange line (left axis) shows the estimates of the autoregressive coefficient of the lagged large cap index returns. Blue line (right axis) shows the estimates of the autoregressive coefficient of the lagged small cap index returns..

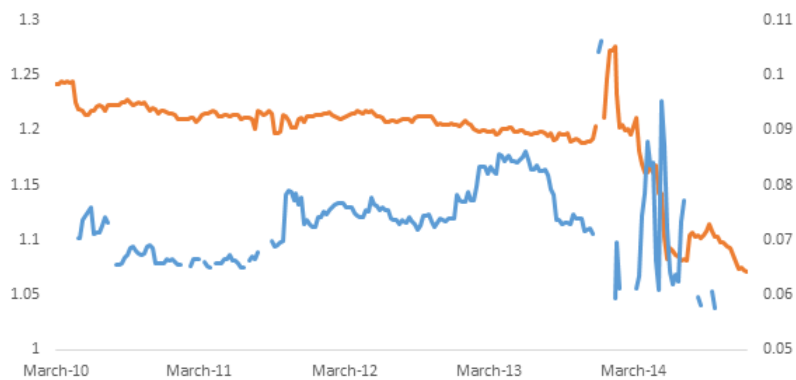
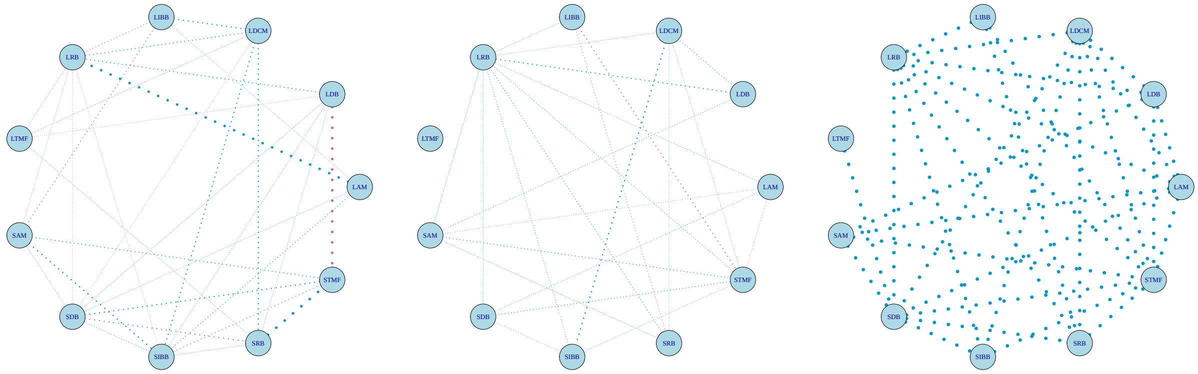


Figure 2: Interaction terms estimates of ϕ_{12}, ϕ_{21} based on eq.(1). Orange line (left axis) shows the interaction between the large cap index and the lagged value of the small cap index returns. Blue line (right axis) shows the interaction between the small cap index and the lagged value of the large cap index returns..



(a) MES . *(b) NetMES .* *(c) Bayesian Net MES.*

Figure 3: Network of Large and Small Sub-Industries Per Systemic Risk Measure.

In this figure, we present the interconnectedness of large and small sub-industries, on the basis of partial correlations between the systemic risk measures for the overall time period. Within each graph, the size of each node represents the magnitude of the systemic risk measure for the specified financial sub-industry. Each node indicates the systemic risk measure for a sub-industry. The link between any two nodes, represents the presence of a significant partial correlation coefficient between them, the thickness of the link line indicates the link magnitude. The more thick the line, the larger is the value of the significant partial correlation and the stronger the link is, also the color of the link indicates whether the partial correlation has a negative value represented by a red color, or a positive indicated by gray color.