Systemic Risk and Financial Connectedness: Empirical Evidence

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1 Introduction

A fundamental characteristic that distinguishes systemic events from idiosyncratic ones are the relation between the system participants. A common sequence of a systemic contagion, is when a supposedly firm specific events becomes transmitted into the cross-sectional dimension. Clearly, the way particular entities are interacting within the system is a key characteristic in order to understand the dynamics and severity of systemic events. This is what separates the common approach to systemic risk, where the stability of the system is but a sum of idiosyncratic risks, to the one that emphasizes the role of system structure. These contrasting distinctions are best captured by the concepts of *too-big-to-fail* and *too-interconnected-to-fail*. Where the former, emphasizes the sheer size of the entity and its potential impact on the system in case of default. On the other hand, the latter term describes the way the system depends on that particular institution, due to its central role within the system. It has been acknowledged that the macroprudential policy was too focused on the sheer size of institutions, but insufficiently on their systemic contribution (see e.g. Bernanke (2009) or Rajan (2009)). That being said, it is crucial to view the system through the lenses of both of these approaches, for they are complimentary when assessing the stability of the financial system.

This approach to the systemic risk, gave a rise to the concept of *robust yet fragile* property of the financial system. In the context of financial markets, the term was first coined[1] by the economist at the Bank of England, Andrew Haldane (Haldane

[1] Before that, the term was commonly used in the complexity science (see e.g. Doyle et al. (2005)

(2013)). He posits, that due to its interconnectedness, the financial system exhibits a tipping point property. The connections among financial institutions serves as a shock absorbers, as long as the extent of the shock is limited. The common links allow for a shock to be spread throughout the network, at the same time suppressing the damages of the initial shock. However, once the extent of the shock exceeds a certain point, the properties of the contagion changes markedly. The network of the institutions no longer works as shock absorber, but as a shock amplifier of the initial disturbance. The damages are transmitted further on, disturbing the banks in a chain reaction. With the final contagion substantially exceeding the degree of the initial shock. The contagion is transmitted akin to the spread of the disease.

A relatively new strain of literature, that incorporates the way institutions are forming the financial networks, have emerged as a response to the increasing connections among the market participants. The literature provides several theoretical models describing the aforementioned property[2]. One of the extension of the property is described in Acemoglu et al. (2015). They provide a simple, yet profound model in which a more densely connected financial network improves the stability of the system when faced by a shock, relatively smaller in magnitude. On the other hand, similarly to the *robust yet fragile* property, beyond some degree of the shock, more dense connections of the system are undermining the stability thereof. Thus, their conjecture highlights, that the network density may have a substantially different effect depending on which regime the markets currently are.

Considering the above theoretical literature, herein work aims at providing an empirical evidence to the regime-dependent effect of the network density on the stability of the financial system. We mostly follow the description of the *robust yet fragile* property as in Acemoglu et al. (2015), however, the evidence is easily applicable to the other models (see Glasserman and Young (2016) for an extensive literature review). To the best knowledge of the authors, there has not been a study that provides an empirical evidence of this phenomenon.

More precisely, our research design is a two-step process. First, we collect a time series of stock prices of the systematically important banks in both US and EU. Based on the data, we estimate the network between the banks and its density in a rolling

and Carlson and Doyle (2002))

[2]In fact, the *robust yet fragile* property of the financial system was described before it was called as such (see e.g Gai and Kapadia (2010), first published in 2008, or Gallegati et al. (2008)).

window basis. In order to achieve robust results, the modeling approach is based on several methods, well established in the literature of network econometrics. This procedure results in a time series of financial connectedness for the particular financial market. In the second step, we estimate a Markov switching ARCH model, where the connectedness is the exogenous, regime-dependent variable. We assume, that a volatility of particular banking index reflects the stability thereof. Additionally, we provide a series of robustness checks, *inter alia*, by including the financial statement data of the banks in the modeling framework.

The model endogenously finds two distinct regimes of the analyzed relationship. The results indeed provide an evidence confirming the set of theoretical models. The effect of the network density on the stability of the financial system varies depending on the regimes. However, the effect is much asymmetrical. During the stable market regime, the network density has almost no effect on the stability of the financial system. At the same time, more dense financial network, is undermining the stability of the system during the unstable market regime[3]. It is, thus, evident that the increased bank interconnectedness is in total a damaging property of the financial markets.

The remainder of the paper is structured as follows. Next section provides a brief literature review and its link to herein paper. Section.......

2 Literature

As the research aims at connecting the theoretical models of the financial networks with the empirical evidence, the relevant literature is divided into theoretical and empirical part.

One of the earliest seminal models describing the contagion through the lens of financial networks was Allen and Gale (2000). Where they arrive to the very intuitive conclusion that a complete network[4] between the banks, is more robust to the contagion than the incomplete one. The mechanism is that the more diversified network of banks allows the liquidity shock to spread among the network. A similar conclusion can be drawn from the work of Freixas et al. (2000), where they emphasize the role of the central bank in coordinating the banking system during the contagion. An important advancement in analyzing financial networks was introduced in Eisenberg and Noe

[3]Acemoglu et al. (2015) describe these regimes as "small shock" and "large shock" respectively.

[4]In graph theory, a complete graph has connections among all of its nodes.

(2001). They provide a method to obtain a clearing vector among the banks, that clears their obligation. Additionally, they prove uniqueness of the vector. The method is extensively used for modeling the contagion in the financial networks and has been extended, e.g. for liquidity consideration (Cifuentes et al. (2005)) or for liquidation costs (Rogers and Veraart (2013)).

Since the first works, modeling banking system as a financial network, there was an increased effort into describing alternative ways of contagion propagation in this framework. One of the very first ones was described in Cifuentes et al. (2005), where the banks are interconnected through common market asset holdings. They show, that when the market's demand for illiquid assets is not perfectly elastic, selling them on the market by the banks may decrease prices substantially. At the same time, due to mark-to-market accounting, other banks with the same holdings may be under pressure to sell their assets, further depressing and generating the fire sales. This contagion may begin even from lesser shocks. Elliott et al. (2014) emphasize the role of bankruptcy cost in amplifying the cascading effect of the contagion. Their model also distinguishes integration from the network connectedness, defining it as a degree of dependence from the network. They show, that although integration can increase the likelihood of a cascade once an initial failure happens, it might also decrease the chance of that first failure. Caballero and Simsek (2013) shows, that once the contagion begin, the banks are facing an increasingly complex environment as they need to monitor the bigger part of the network in order to control their own default risk. This uncertainty induced counterparty risk causes precautionary behavior among banks, further exacerbating the fire sale.

A considerably more relevant strain of literature to herein research considers the nonlinear effect of the connectedness on contagion dynamics. Based on previously studied concept of percolation on random graph from complexity science (Callaway et al. (2000) or Newman et al. (2001)), Gai and Kapadia (2010) show that the financial system exhibits a similar form of phase transition. Specifically, due to the dense structure of the financial networks, the likelihood of contagion is particularly low. However, the same property makes the contagion very severe once it happens. Based on the same model, May and Arinaminpathy (2010) apply mean-field approximation, to identify the contribution of various parameters in the model to the likelihood and severity of the contagion. An already mentioned research of Acemoglu et al. (2015), goes beyond the model of Gai and Kapadia (2010). They suggest, that the degree of connectedness of the financial system have a regime-dependent effect on stability, at the same time proving the narrative of Andrew Haldane (Haldane (2013)). The contribution of herein research is exactly to provide an empirical evidence of their work as well as the intuition of policymakers.

Since the work is mostly empirical in nature, it is also imperative to position it among the literature of network econometrics. Although scarce in data, there has been several works statistically describing the actual transaction level data[5] and thus, the network among the banks. Using Bundesbank data on bilateral interbank exposures among 2000 banks from 1999 to 2012, Craig and von Peter (2014) provide evidence for tiering on the interbank market. The banks are forming a very hierarchical network, where a lower-tiered banks are interacting between each other mostly through the intermediating banks, mostly bigger in size[6]. The tiering behavior is modeled and commonly referred to in the literature as a *core-periphery* structure. Based on the Italian interbank market data from January 1999 to December 2010, Fricke and Lux (2015) confirm previous contribution, at the same time showing, that the core of the financial network is highly persistent in time. That is, the banks forming the core don't change the position in the structure. Langfield et al. (2014) extend the previous research with the data across other class of assets held among the banks (such as derivatives, marketable securities, repo, unsecured lending and secured lending). They emphasize particular heterogeneity of the financial network, by distinguishing between interbank funding and interbank exposures. The structure is significantly different among these types, thus the dynamics of contagion varies depending on the source of risk (liquidity vs. credit risk). Clearly, the contribution of this part of the literature is mostly in describing the stylized facts present in the actual financial networks.

As much as the network data is available (although to the very limited extent), the econometricians aimed at estimating the financial networks from broadly available sources, mostly from equity price time series. Billio et al. (2012) describe a pair of econometric methods, that are employed as part of this work. They use monthly stock prices of insurers, hedge funds and banks to estimate their interconnectedness. In the first approach they suggest a model based on principal component analysis (Herafter

[5]The data is often proprietary to the public entities regulating the financial markets.

[6]A similar behavior is also present in other economic networks e.g. international trade (Antras and Costinot (2011))

referred to as PCA, Muirhead (2009)). When used on the covariance matrix of stock returns, the PCA will provide a set of factors eigenvalues best describing the variation of the system. A higher share of the variance, explained by top eigenvalues, indicates elevated connectedness in the system. A second model provides more detailed information by estimating a whole directed network of the financial institutions. The method is based on the "Granger causality" (Granger (1969)) among the pair of allegedly connected entities. The financial network is constructed by performing the granger test on each of pairs of the stock returns with adjacency matrix entries being one or zero depending on the outcome of the test. The resulting approach allows higher flexibility in analyzing the topology of the network and deciding the measures of connectedness (the authors use a range of different network measures). These methods are employed in the research design and more closely described later on.

Alternative methodology to estimate financial networks from the stock prices data was developed by Diebold and Yılmaz (2014). In their work, the financial network[7] is estimated as a matrix of parameters from the Vector Autoregression model (Sims (1980)). Precisely, the adjacency matrix of the network is the Θ from the VAR matrix notation: $\boldsymbol{y}_t = \theta_o + \boldsymbol{\Theta}\boldsymbol{y}_{t-1} + \epsilon_t$. In a similar vein to Billio et al. (2012), the authors use their method to estimate the network and appropriate connectedness measures among the financial institutions from USA[8]. As these methods may seems to be substitutable at first, the authors themselves point out the differences between their approach and that of Billio et al. (2012). Considering the VAR methodology, it is evident that the resulting network of connections is weighted, unlike the Granger-based approach. This provide another dimension to analyze the strength of the links among the institutions. Moreover, at least in the standard formulation, the Granger-based approach is only pairwise. That is, it does not control for the spurious relationship, stemming from the confounding third (or more, in that matter) entity. However, the Granger-based method is flexible enough to extend the main regression used to test the Granger causality by more control variables. There are, of course, some disadvantages to rely on the VAR approach. It requires identifying assumptions, related to the variance decomposition.

[7]Or in the paper's terminology - a connectedness table.

[8]The same approach was applied also to other data. For example, international trade (Diebold and Yilmaz (2023)) commodities (Diebold et al. (2017) and Gong and Xu (2022)), cryptocurrencies (Ji et al. (2019)), particular pair of countries (Dadej (2023)) and among the whole asset classes (Bouri et al. (2021)).

Also, what is more relevant to the herein research is higher computational burden coming from the VAR approach. Given, that the research design does not require information on link weights and is computationally expensive, the approach of Billio et al. (2012) was considered to be more appropriate.

There is a number of alternative methods used for estimating networks in general, but more often used in other fields of study. A common approach from systems biology are Gaussian graphical models (e.g. applied in Friedman (2004)). They allow for maximum likelihood estimation with penalization, producing a robust network estimation. Some of the applications in finance were estimating international finance flows (Giudici and Spelta (2016)) or systemic risk on the banking sector (Cerchiello and Giudici (2016)). Barigozzi and Brownlees (2019) employs common approach to estimate network with VAR, but they extend the methodology with LASSO estimation (Breiman (1995)), allowing for sparsity of the network and improved forecasting.

Another strain of literature, suggesting the methods to estimate financial networks, comes from a different data source. Banks do not provide counterparty information in their financial statements but they do show their aggregated values for both lending and borrowing on the interbank market. This is a source of hard data that provides the marginal values for the adjacency matrix of the network, i.e. the columns and rows sums. Several authors provided methods of filling the adjacency matrix at the same time satisfying some stylized facts regarding financial networks. The stylized facts are provided by the research based on the actual data (surveyed before in herein section) or commonly accepted economic rationale, in case of no self-lending restriction. One of the most common approach is to estimate the network as evenly as possible. This method, know as *maximum entropy* (Upper (2011)), assumes that banks are trying to diversify their holdings as much as possible. The supposition that banks are diversifying as much as posible, may seems appealing at first. However, due to the monitoring costs and informal relationships (Bräuning and Fecht (2016)) among banks (Cocco et al. (2009)), it is not realistic. Most likely overestimating density of the actual financial network. Having that in mind, Anand et al. (2015) suggest a *minimum density* method which minimizes the total number of linkages necessary for allocating interbank positions. An appealing characteristic of the method is that it is overestimating the degree of contagion (according to the author's comparison). This is contrary to the benchmark methods, which more often underestimate it. A method suggested by Baral and

Fique (2012), draws a link weights based on the copula distribution fitted to the aggregated interbank data. Cimini et al. (2015) uses fitness model based on likelihood of directed connections with additional knowledge of the node's parameters. Drehmann and Tarashev (2013) takes into account a commonly recognized stylized fact regarding the interbank market, that the network exhibits a *core-periphery* structure. Their method provides a reconstructed matrix with *core-periphery* characteristic. Hałaj and Kok (2013) suggest an iterative method were the network links are drawn randomly until the network is reconstructed. Above methods are compared together in a horse race described in Anand et al. (2018).

A literature considering connections between financial institutions in the context of systemic risk and contagion is vast. Considering the increased importance of connectedness for assessing the systemic risk, Hautsch et al. (2014) improve on the works of Adrian and Brunnermeier (2016) to propose the realized systemic risk beta. The measure specify the contribution of particular financial institution to the systemic risk, given its position in the network. A similar metric is suggested by Dungey et al. (2012). They rank financial institutions in order of their systemic importance, considering their correlation-based connectedness. Savona (2014) estimate dynamic conditional correlation model, in order to study the contagion among the hedge funds. The author shows, that correlations are key factor for predicting depressed hedge fund returns. A broader perspective is shown in the work of Minoiu et al. (2015). According to their research, an elevated country connectedness, and at the same time, decrease in those of its neighbors, is able to predict the banking crisis.

3 Data

The main set of results is based on the equity stock prices and indices data. The stock data is adjusted for corporate actions such as splits and dividends. The analysis focus on the data of financial institutions from two biggest financial sectors. Namely, that of United States and European Union. An exact list of the institutions follows the stress test exercises from both of the banking sectors analyzed (European Banking Authority (2021) and Federal Reserve system (2021)). The number of institutions is 31 and 42 for USA and EU respectively. The full list is presented in the table 2 in the appendix A. Not every company was listed from the beginning of the analyzed period. The list of the first available price data (thus including in the analysis) is presented in table 3 in the appendix A. Additionally, the relevant banking indices are used as a proxy of financial stability (KBW Nasdaq Bank Index and EURO STOXX® Banks) and broad market indices for control (S&P500 and STOXX® Europe 600). A robustness check incorporates financial statements of the institutions into analysis. The financial variables are obtained from Orbis database for each quarter between 2017Q3 and 2024Q4[9]. The source of the data is Yahoo Finance.

3.1 Summary statistics

Table 1 reports descriptive statistics of the stock price data for both of the markets. On average the stock prices have a (slight) upward trend with average return being positive and similar for both of the markets. Although, once the sample is split pre and post Great Financial Crisis (hereafter referred to as GFC), there are substantial differences. The average returns are higher post-GFC for USA than before, au contraire, the European returns were higher pre-GFC. It clearly shows, the banking dimension of the debt crisis that hit the Europe in the second decade of 21st century. It is also evident that the European market is more volatile. Every dispersion measure is higher for EU than USA. This is as expected, considering the more severe banking crises in a lot of European member states (e.g. Greece, Italy and Ireland). Unlike in the USA, where there was no substantial banking contagion after the 2008 subprime crisis.

The American market is on average more correlated than the European one. The reason is more fragmented banking sector[10] in Europe, with different member states having a separate banking law, regulators, capital markets and in general a more heterogeneous real economy. That being said, the systemic risk of the banking sector is indeed a EU-wide concern (see e.g. Song and Zhang (2021)).

4 Financial network Connectedness

Because of lack of public data from the interbank market, or as a matter of fact, any bilateral contractual obligations between the banks, the academic literature developed a set of tools to estimate the financial networks from available sources. As shown in the literature, these methods are well established and commonly applied in order to

[9]However, due to missing reports for some institutions the actual data used is smaller

[10]Although, the concept of Banking union is discussed.

market	EU	USA
Average return (%)	0.0395	0.0412
Std. deviation (%)	3.83	2.49
max drawdown (%)	-88.77	-83.17
1% percentile (%)	-7.55	-6.63
99% percentile (%)	7.76	6.99
worst return (%)	-93.33	-59.03
max return (%)	1400	86.9
Average correlation	0.398	0.617
Sample size	5748	5844

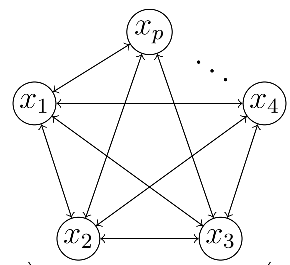
Table 1: Descriptive statistics of the data. The statistics are averages over stock returns and markets. In case of maximum and minmium values, the minimum (for stocks) of the minimum (for each market) and vice versa for the maximum.

estimate the financial connections. This is despite some of their limitations. One may wonder, how can the stock prices reflect an information that is not public? There is however, evidence, that the stock prices discount also some unknown information to the public, e.g. due to insider trading or inferred from other data. A classic example is Newhard (2014), describing the, allegedly, the first ever event study performed on the stock prices. Based on the outperformance of lithium producers he inferred the fuel material used in the manufacturing of the newly-developed hydrogen bomb. An information which was non-public, to the extent, that his paper was confiscated. The literature on insider trading and non-public information on the stock market is vast and extends beyond the scope of herein paper (see e.g. Haw et al. (1990), Huddart et al. (2007) or Klein et al. (2020)). As well as assessment of the methods to estimate the financial network.

A schematic representation describing the problem faced by both Billio et al. (2012) and Diebold et al. (2017) of financial network estimation is shown in the Figure 1. Based on the multivariate time-series data matrix X, consisting of stock price returns, the authors suggest a method of infering an adjacency matrix, describing the connections among the financial institutions. As shown, the adjacency matrix has a number of columns and rows equal to the number of entities. Each of the elements in the adjacency matrix $\boldsymbol{A}$, describe the connections between the entities. That is, $a_{i,j} > 0 \Rightarrow i \rightarrow$

$$\underbrace{\begin{pmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ x_{31} & x_{32} & \dots & x_{3n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{T1} & x_{T2} & \dots & x_{Tn} \end{pmatrix}}_{\text{Time series matrix } \boldsymbol{X} \text{ of size } T \times n.} \xrightarrow{f: \mathbb{R}^{T\times n} \to \mathbb{R}^{n \times n}} \underbrace{\begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{pmatrix}}_{\text{Adjacency matrix } \boldsymbol{A} \times n.}$$

$$||$$



Graph representation of matrix $\boldsymbol{A}$.

Figure 1: Scheme describing the process of financial network estimation.

$j \ \forall \ i \neq j$. In the economic applications, the diagonal values are usually zero, as there is no intuition behind a self connection of a financial institution. Each $a_{i,j}$ can take binary values in case of unweighted graph or any other real-valued number in case of weighted graph. A very useful property, linking linear algebra and graph theory is that every graph has its own adjacency matrix (and vice versa). Thus, a variety of graph theory measures may be applied to the estimated network of connections. One of the most common measure describing the financial connectedness is the average degree, which is average number of edges each of the graph nodes has. The measure may provide a single value number describing the connectedness of entirety of financial system (at least so far as goes the number of included financial institutions).

In what follows in the section, the particular methods of estimating the financial networks are described. Out of the three methods employed in the research design, the last two of the them follows the work of Billio et al. (2012). With the first one suggested by the author.

4.1 Ledoit-Wolf covariance

This approach follows a commonly applied in finance (and in portfolio optimization in particular) shrinkage method suggested by Ledoit and Wolf (2003).The idea behind shrinkage is to compute the convex linear combination of sample covariance $\hat{\Sigma} = \frac{1}{N}\boldsymbol{X}'\boldsymbol{X}$ (with elements $\hat{\sigma}_{i,j}$) of rates of returns matrix $\boldsymbol{X}$ and an identity matrix $\mathbb{I}$:

$$\tilde{\Sigma} := \rho_1\mathbb{I} + \rho_2\hat{\Sigma} \tag{1}$$

The optimal linear combination above is the solution to the following quadratic program subject to linear constraint:

$$\begin{aligned} \max_{\rho_1,\rho_2} \quad & \mathbb{E}[||\tilde{\Sigma} - \Sigma||^2] \\ \text{s.t.} \quad & \tilde{\Sigma} = \rho_1\mathbb{I} + \rho_2\hat{\Sigma} \end{aligned} \tag{2}$$

Where the $||\cdot||$ is the Frobenius norm defined[11] as $||A|| = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N} a_{i,j}^2}$. With solution equal to:

$$\tilde{\Sigma} = \frac{\beta^2}{\delta^2}\mu\mathbb{I} + \frac{\alpha^2}{\delta^2}\hat{\Sigma} \tag{3}$$

The estimators of β^2, δ^2, α^2 and μ being:

$$\begin{aligned} \hat{\mu}_T &= \frac{1}{N}\sum_{i=1}^{N}\sigma_{i,i}^T \\ \hat{\delta}_T^2 &= ||\hat{\Sigma}_T - \hat{\mu}_T\mathbb{I}_T||^2 \\ \hat{\beta}_T^2 &= \min\left\{\frac{1}{T}\sum_{t=1}^{T}||x_t^T(x_t^T)' - \hat{\Sigma}_T||^2,\, \hat{\delta}_T^2\right\} \end{aligned} \tag{4}$$

Once the shrinked covariance matrix is estimated, it is assumed to reflect the underlying connections among the financial institutions. The connectedness is thus measured as an average Ledoit-Wolf covariance among the entities:

$$\gamma_{LW} = \frac{\sum_{i\neq j}^{N}\sum_{j\neq i}^{N}\tilde{\sigma}_{i,j}}{N^2 - N} \tag{5}$$

Where $\tilde{\sigma}_{i,j}$ are, as before, elements of the matrix $\tilde{\Sigma}$.

[11] For the purpose of this exercise, this is a slightly modified version of the Frobenius norm.

The procedure tends to pull the most extreme paraemters into more central values, thus systematically reducing estimation error. The estimation error is especially substantial when the dimension of the analyzed data is high, with respect to the amount of observations available. another work by the original authors Ledoit and Wolf (2004) performs a Monte Carlo simulation study benchmarking alternative ways to estimate the covariance matrix and shows the superiority of their approach for large dimensional data. This is considerably relevant considering research design of this work. As mentioned before, the connectedness measure will be calculated in a rolling window basis. Often as small as a single quarter (63 observations vs. 42 variables).

4.2 Principal component analysis

A connectedness measure based on the principal component analysis (PCA) is the first method suggested by Billio et al. (2012). The idea is to calculate the share of variance explained by the top k component. In principle, the PCA is the eigendecomposition of a covariance matrix (with variance of covariates scaled to one). Namely, we wish to find an eigenvector ν and eigenvalue λ that satisfy following equation:

$$\hat{\Sigma}\mathbf{v} = \lambda\mathbf{v} \tag{6}$$

The values of interest may be find solving a homogeneous system of linear equations $|\hat{\Sigma} - \lambda\mathbb{I}| = 0$, with $|\cdot|$ being a determinant operator. An important property of the eigenvectors is their orthogonality. The covariance matrix is decomposed in a following way:

$$\hat{\Sigma} = \mathbf{Q}\mathbf{\Lambda}\mathbf{Q}' \tag{7}$$

Where $\mathbf{\Lambda} = \text{diag}\{\lambda_1, \lambda_2, \ldots, \lambda_n\}$ and $\mathbf{Q}$ is an orthogonal matrix whose columns are unit eigenvectors. Thus, the eigendecomposition yields a set of uncorrelated components fully explaining (linearly) the underlying covariance matrix. The eigenvalues reflect the variance explained by the relative eigenvector.

In the context of the data used in this research, the biggest eigenvalue shows the amount of variance of the returns, explained by the most important factor. Thus, the relevant measure of the connectedness is:

$$\gamma_{PCA} = \frac{\max\{\lambda\}}{\lambda'\mathbf{1}} \tag{8}$$

Where **1** is a vector of ones with appropriate size. The measure may be interpreted as a share of the single most important component in explaining the total sum of the variances. It is clear, that the measure have some drawbacks when analyzing connectedness. The procedure does not yield the connections among the institutions (other than covariance itself) but a single measure of connectedness. Notwithstanding this disadvantage, the measure is useful in the context of herein research design, as the main objective of this stage is to obtain the single connectedness measure.

4.3 Granger based connectedness measure

The approach, that yields not only a network of the connections but also its directionality is based on the concept of Granger causality (Granger (1969)). The variable x_t is said to "Granger-cause" a variable y_t if it contains enough information at time $t-1$ to predict the respective variable in the next period t. Naturally, this statement is tested by running a regression with lagged variable:

$$y_t = \beta_0 + \beta_1 x_t + \underbrace{\sum_{i=1}^{p} \beta_{i+1} y_{t-p}}_{\text{lag controls}} + \epsilon_t \tag{9}$$

Where β are the estimated coefficients and ϵ_t the error term. The variable x_t Granger-cause y_t if the respective coefficient β_1 is significantly different from zero. In the context of financial markets, the above approach may appear to be implausible to a lot of financial economists. That is because of the relatively high degree of information efficiency, considering we analyze the most liquid markets in the world. This efficiency implies that any publicly accessible information should yield no predictive ability, thus rendering the equation 9 pointless. That being said, the test indeed finds the underlying connections [12]. This is due to several factors. The primary one, is that the statistical significance is not equal to the economical one. Any execution of potential strategy following the equation 9, will stumble upon the transaction costs, including slippage and commisions, which will make the exercise unprofitable. Thus, the granger causality may just as well be seen as a return spillover between the institutions, as shown in Battiston et al. (2012).

[12] Even with a frequency higher than the applied confidence interval.

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A Data

USA		EU		
Ticker	Name	Ticker	Name	Country
BAC	Bank of America Corporation	EBO	Erste Group Bank AG	Austria
BK	The Bank of New York Mellon	RAW	Raiffeisen Bank AG	Austria
BCS	Barclays*	KBC	KBC Group	Belgium
BMO	Bank of Montreal*	CBK	Commerzbank AG	Germany
COF	Capital One Financial Corporation	DBK	Deutsche Bank AG	Germany
SCHW	The Charles Schwab Corporation	NDA-SE	Nordea	Finland
C	Citigroup	DANSKE	Danske Bank A/S	Denmark
CFG	Citizens Financial Group	JYSK	Jyske Bank A/S	Denmark
DB	Deutsche Bank*	SYDB	Sydbank A/S	Denmark
GS	The Goldman Sachs Group	BBVA	Banco Bilbao Vizcaya	Spain
JPM	JPMorgan Chase & Co.	BKT	Bankinter SA	Spain
MTB	M&T Bank Corporation	CABK	CaixaBank SA	Spain
MS	Morgan Stanley	SAB	Banco de Sabadell SA	Spain
NTRS	Northern Trust Corporation	SAN	Banco Santander SA	Spain
PNC	The PNC Financial Services Group	UNI	Unicaja Banco SA	Spain
STT	State Street Corporation	BNP	BNP Paribas SA	France
TD	The Toronto Dominion Bank*	ACA	Crédit Agricole SA	France
TFC	Truist Financial Corporation	GLE	Société Générale	France
UBS	UBS Group AG*	ALPHA	Alpha Services and Holdings SA	Greece
WFC	Wells Fargo & Company	EUROB	Eurobank Ergasias	Greece
ALLY	Ally Financial Inc.	ETE	National Bank of Greece SA	Greece
AXP	American Express Company	TPEIR	Piraeus Financial Holdings SA	Greece
DFS	Discover Financial Services	OTP	OTP Bank Nyrt	Hungary
FITB	Fifth Third Bancorp	A5G	AIB Group plc	Ireland
HSBC	HSBC Holdings plc*	BARC	Barclays PLC	Great Britain
HBAN	Huntington Bancshares Incorporated	BARC	Barclays PLC	Great Britain
KEY	KeyCorp Bank	BIRG	Bank of Ireland Group	Ireland
MUFG	Mitsubishi UFJ Financial Group*	BAMI	Banco BPM S.p.A.	Italy
PNC	The PNC Financial Services Group	ISP	Intesa Sanpaolo S.p.A.	Italy
RF	Regions Financial Corporation	MB	Mediobanca Banca di Credito Finanziario S.p.A.	Italy
SAN	Banco Santander, S.A.*	BMPS	Banca Monte dei Paschi di Siena S.p.A.	Italy
		BPE	BPER Banca S.p.A.	Italy
		UCG	UniCredit S.p.A.	Italy
		ABN	ABN AMRO Bank N.V.	Netherlands
		INGA	ING Groep N.V.	Netherlands
		DNB	DNB Bank ASA	Norway
		PKO	Powszechna Kasa Oszczednosci Bank Polski S.A.	Poland
		PEO	Bank Polska Kasa Opieki S.A.	Poland
		BCP	Banco Comercial Português S.A.	Portugal
		SEB-A	Skandinaviska Enskilda Banken AB	Sweden
		SHB-A	Svenska Handelsbanken AB	Sweden
		SWED-A	Swedbank AB	Sweden

Table 2: List of the banks analyzed. *These banks are not registered in USA but are apparently systematically important to the local market according to the regulator.

USA		EU	
Ticker	IPO date	Ticker	IPO date
ALLY	2014-01-29	A5G	2000-01-06
AXP	2000-01-06	ABN	2015-11-23
BAC	2000-01-06	ACA	2001-12-17
BCS	2000-01-06	ALPHA	2000-01-06
BK	2000-01-06	BAMI	2000-01-06
BMO	2000-01-06	BARC	2000-01-06
C	2000-01-06	BBVA	2000-01-06
CFG	2014-09-25	BCP	2000-01-06
COF	2000-01-06	BIRG	2001-07-16
DB	2000-01-06	BKT	2000-01-06
DFS	2007-06-15	BMPS	2000-01-06
FITB	2000-01-06	BNP	2000-01-06
GS	2000-01-06	BPE	2000-01-06
HBAN	2000-01-06	CABK	2007-10-11
HSBC	2000-01-06	CBK	2000-01-06
JPM	2000-01-06	DANSKE	2000-11-09
KEY	2000-01-06	DBK	2000-01-06
MS	2000-01-06	DNB	2000-01-06
MTB	2000-01-06	EBO	2009-03-31
MUFG	2001-04-03	ETE	2000-01-06
NTRS	2000-01-06	EUROB	2000-01-06
Open	2000-01-06	GLE	2000-01-06
PNC	2000-01-06	INGA	2000-01-06
RF	2000-01-06	ISP	2000-01-06
SAN	2000-01-06	JYSK	2004-10-05
SCHW	2000-01-06	KBC	2000-01-06
STT	2000-01-06	MB	2000-01-06
TD	2000-01-06	NDA	2000-01-06
TFC	2000-01-06	OTP	2002-03-06
UBS	2000-05-17	PEO	2000-01-06
		PKO	2004-11-11
		RAW	2010-08-17
		SAB	2000-01-06
		SAN	2000-01-06
		SEB	2000-01-06
		SHB	2000-01-06
		SWED	2000-01-06
		SYDB	2000-01-06
		TPEIR	2000-01-06
		UCG	2000-01-06
		UNI	2017-07-03

Table 3: First available data for each of the stock prices.