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Mapping the stocks in MICEX: Who is central to the Moscow Stock Exchange?*

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Abstract

In this article we use partial correlations to derive bidirectional connections between major firms listed in the Moscow Stock Exchange. We obtain coefficients of partial correlation from the correlation estimates of the Constant Conditional Correlation GARCH (CCC-GARCH) and the consistent Dynamic Conditional Correlation GARCH (cDCC-GARCH) models. We map the graph of partial correlations using the Gaussian Graphical Model and apply network analysis to identify the most central firms in terms of both shock propagation and connectedness with others. Moreover, we analyze some network characteristics over time and based on these we construct a measure of system vulnerability to external shocks. Our findings suggest that during the crisis interconnectedness between firms strengthens and becomes polarized and the system becomes more vulnerable to systemic shocks. In addition, we found that the most connected firms are the state-owned firms Sberbank and Gazprom and the private oil company Lukoil, while in the top most central in terms of systemic risk contributors Sberbank gave its place to NLMK Group.

Keywords: Multivariate GARCH, Volatility Spillovers, Network connections, MICEX

JEL Classification: C01, C13, C32, C52

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1 Introduction

The financial crisis of 2008 exposed the need for a better understanding of risks in financial markets and in economies in general. More specifically, systemic risk became one of the most important issues and encouraged a lot of literature in finance mainly after the crisis of 2008. There are several approaches to measure systemic risk, such as the SRISK proposed by Brownless and Engle (2016) or the CoVaR method by Adrian and Brunnermeier (2016) among many others.

Linkages between firms is one of the key channels by which systemic risk spreads throughout the system. Once a firm experiences a negative shock, the value of it falls and it becomes dangerous not only for the firm and its stockholders, but it might also negatively affect the whole economy through trading or loan channels. Hence, estimating these connections plays a central role in understanding the behaviour of such systemic risk. A widely used approach to describe the connectedness among a number of companies is the use of graphs as a network theory application. Moreover, network theory helps us not only to visualize the graph of connectedness but also to analyze interrelations based on different network measures.

There are a number of papers, that describe and analyze financial and economic interrelations from the network theory perspective. For example, Acemoglu et al. (2012) show that the level of aggregate fluctuations in an economy depends on the structure of the intersectoral network; that is, idiosyncratic shock in sectors might not cancel out through diversification. Battiston et al. (2012) use network representation of financial system to extend the meaning of "too big to fail" institutions to "too central to fail". In order to identify such central institutions they proposed DebtRank measure of systemic impact based on the centrality measures of financial graphs. Following the similar idea of centrality implementation and using the concept of partial correlations, Anufriev and Panchenko (2015) found strong connections between several Australian banks and determined which banks play a central role in the shock propagation. Diebold and Yilmaz (2014) modeled time-varying network of financial institutions in the US including the period of the financial crisis based on the variance decomposition measure. For more examples of the network modeling and, in particular, of the network application to systemic risk modeling we refer to the recent surveys of Bougheas and Kirman (2015), who review studies on the measurement of systemic risk mainly with network tools, and Iori and Mantegna (2018), who focuses on empirical analyses of networks in finance.

In our paper we identify top connected firms and top systemic contributors using static and dynamic models in the Russian Stock Market. In addition, we calculate the vulnerability index of the system through a principal components analysis of the measures that summarizes the network. This magnitude can be used as a measure of overall systemic risk in the entire economy, as it shows the sensitivity of the system to negative shocks in general.

In order to construct a network of connectedness, we use the Gaussian Graphical Model (GGM) approach, which is quite new for finance, although it is widely used in biometrics (see for example Krumsiek *et al.*, 2011; Rice *et al.*, 2005). The idea of the GGM is to capture the linear bidirectional dependence between two variables measured via partial correlations conditional on other elements in the system. The linear dependence between a pair of firms represented by a partial correlation shows how these firms co-move under market conditions and different externalities. The GGM allows us to construct a graph of interconnectedness between components of a multivariate random vector. The nodes of a graph represent the elements of this multivariate vector and the edges show their conditional dependence. This type of network of partial correlations between firms shows not only how well the whole economy is connected, but also how the market co-moves with a company suffering from a negative exogenous shock.

Firms can be connected in different ways. For example, they can be connected directly via trading relationships or they can have the same intermediary firms in their production chains. However, to study interconnectedness in a financial market we need more frequent data, than, for instance, company balance sheets. One of the convenient ways to identify connectedness between firms is to consider co-movements of their stock returns (see Diebold and Yilmaz, 2014). The idea of this approach is that almost all firms, especially the largest ones, spend a lot of resources in order to manage their businesses in accordance with concurrent market conditions, and virtually all their decisions affect their stock prices. That is why connectedness between stock returns can be taken as a proxy for the true unobservable connections between firms. Moreover, such frequent data allows us to calculate a daily measure of systemic risk, which is a considerable advantage for policymakers.

In this paper, we use an approach similar to that of Anufriev and Panchenko (2015), while taking some ideas from Barigozzi and Brownlees (2016) and Diebold and Yilmaz (2014). One novelty of our work is in the econometric methodology. We use a VAR model and Kalman filter to eliminate unobservable common factor. According to Barigozzi and Brownlees (2016), common factors, which affect all the return series will lead to spuriously high correlations and a fully connected network unless they are filtered out. Moreover, we compute partial correlations from the conditional correlation estimates obtained from the Constant Conditional Correlation GARCH model of Bollerslev (1990) and the consistent Dynamic Conditional Correlation GARCH model of Aielli (2008). Given that we use the partial correlations derived from these models for the GGM, the former model provides an idea of how the firms are connected throughout the data period, while the latter model allows us to pinpoint the connections on a certain date. Therefore we can comment on how the network connections restructure in reaction to influential changes. Finally, we use the composite likelihood method of Engle *et al.* (2008) for the estimation. This method successfully avoids the trap of attenuation biases observed in the cDCC-GARCH model.[1] We also discuss an index of vulnerability which we derive based on measures that summarize the network of stocks.

To the best of our knowledge, this is the first work examining major firms in the Russian Stock Market. Our data spans four years of observations and covers in particular 2014, when Russia faced a number of problems.

The paper is structured as follows. Section 2 introduces the network construction based on the Gaussian Graphical Model. Section 3 discusses the crucial measures of network analysis. In Section 4 we introduce our data and in the Section 5 we discuss the econometric models. Section 6 describes the estimation procedure of the econometric models. Section 7 shows the empirical application for the Russian Stock Market. Section 8 provides further discussion of the vulnerability measure and the unobservable factor. Finally, Section 9 concludes the paper.

2 Network construction

Let us consider a graph $G = (V, E)$ with a set of vertices $V = \{1, ..., n\}$ and a set of edges $E = V \times V$. If nodes i and j are connected then pair $(i, j) \in E$. Based on the type of edges, a graph can be directed or undirected as well as weighted or unweighted. In our work we focus on undirected weighted graphs meaning that if pair $(i, j) \in E$, then $(j, i) \in E$, and each edge has a non-zero weight $w_{ij} = w_{ji}$ that shows the strength of connectedness between nodes i and j.

To construct a network, we use the concept of the Gaussian Graphical Model (GGM) based on the works of Buhlmann and van de Geer (2011), Hastie *et al.* (2009) and Anufriev and Panchenko (2015). The GGM helps to construct a conditionally independent weighted graph $G = (V, E)$ with the Markov property that if nodes i and j are conditionally independent then $(i, j) \notin E$. The vertices of the graph correspond to each component of the multivariate random variable $X = \{X_1, ..., X_n\}$.

According to the GGM, the coefficient of partial correlation can be used to measure the conditional dependence between any two nodes. Partial correlation between nodes i and j, that is between components X_i and X_j of the multivariate variable X, is denoted by $\rho_{ij|\cdot}$, and it measures their linear dependence excluding the influence of the rest of the components of variable X. The idea is that while ordinary correlation can show a high connection between

[1] When the number of series in consideration is large, quasi-maximum likelihood estimators of a cDCC-GARCH model with variance targeting yields downward biases in the correlation coefficient estimates, hence implying very little variation in the correlations between returns over time. See Engle *et al.* (2008) for details.

two variables generated by the dependence of these two variables on a third one, the partial correlation measures their connection eliminating the influence of the third variable from both of them. Therefore, the two nodes are connected $(i, j) \in E$ if and only if they are not conditionally independent, that is $\rho_{ij|\cdot} \neq 0$. Moreover, partial correlation between any pairs of nodes is used in the GGM as a weight for an edge in the graph corresponding to that pair, in other words $w_{ij} = \rho_{ij|\cdot}$ is the weight of the edge between nodes i and j.

While ordinary correlations are related to the elements of covariance matrix Ω, the inverse of the non-singular covariance matrix $K = \Omega^{-1}$ contains information on partial correlations. A well-known result (Buhlmann and van de Geer, 2011; Hastie *et al.*, 2009) is that partial correlation can be derived as

$$\rho_{ij|\cdot} = -\frac{k_{ij}}{\sqrt{k_{ii}k_{jj}}} \tag{1}$$

where $k_{i,j}$ is the ij-th element of the matrix $K = \Omega^{-1}$, also called the concentration matrix. The matrix of partial correlations can be expressed similarly as follows:

$$P = -D_K^{-1/2} K D_K^{-1/2}. \tag{2}$$

Moreover, it has been shown that this equation also holds for $K = R^{-1}$(for details see Anufriev and Panchenko, 2015), that is the matrix of partial correlation can be obtained through the matrix of ordinary correlation.

The other common way to represent a graph is via an adjacency matrix (Jackson, 2008). An adjacency matrix A is of size $n \times n$ with a non-zero ij-th element if the nodes i and j are connected and otherwise with zeros. For an undirected weighted graph the adjacency matrix is symmetric matrix with entries given by weights between the appropriate nodes. In the case of the GGM the adjacency matrix contains coefficients of partial correlation $\rho_{ij|\cdot}$ as the ij-th element for $i \neq j$ and zeros on the diagonal. Notice that the diagonal elements of the matrix of partial correlations are minus units given that equation (1) holds. That is, in the matrix form we have:

$$A = I + P = I - D_K^{-1/2} K D_K^{-1/2} \tag{3}$$

where I is the identity matrix of size n and K can be either the inverse ordinary correlation matrix R^{-1} or the inverse covariance matrix Ω^{-1} of multivariate vector X. The adjacency matrix gives us not only a method to set up a graph but an opportunity to analyze the graph using the tools of linear algebra. Our attention focuses on such an analysis in the next section.

From the finance perspective a network of partial correlation provides us with information on the return co-movements of each pair of firms conditional on others. It should be noted that partial correlation does not show the direction of causality, hence we cannot say that, for example, the fall of one company leads to the collapse of its neighbours. However, if we observe that one company faces some negative externalities, then its adjacencies might also be affected by this shock directly or/and through the first firm. In other words, there are three possible reasons for a connection to occur between a pair of firms expressed as the positive partial correlation: (i) a firm affects a second firm, (ii) conversely, the second firm affects the first one, and (iii) they are both influenced by some external factor. An example of the latter possibility might be seen within one sector when firms are connected due to sector-specific common factors.

Finally, the signs of the entries of adjacency matrix, which are constructed based on partial correlation, are important. In network theory weights of edges are usually positive. However, as partial correlations can take values between -1 and 1, some entries of adjacency matrix A can be negative; therefore we cannot simply assume that the weights of the network are positive in the case of the GGM. In social networks the negative values of edges correspond to the relationship between foes, while positive values correspond to the relationship between friends, and an individual can have both friends and foes (see, for example, Kunegis *et al.*, 2009). In finance such relations might be rare. Barigozzi and Brownlees (2016) found some negative edges in the network of U.S. Bluechips constructed with the help of partial correlations and Granger causality, although these negative edges were considerably outnumbered by the positive ones.

In our paper we obtained both positive and negative connections. Therefore, we consider negative edges to be similar to the relationship between competitors, that is the negative value of a partial correlation between two firms means that the rise of one company can encourage (or can be encouraged by) the fall of another firms. As we will see from the empirical results, these negative connections occur more often between firms from different sectors rather than one sector, where companies might directly compete with each other. In the following section we describe network analysis with respect to the graph with both negative and positive links.

3 Network analysis

One of the advantages of using network theory is that it can give us both the numerical characteristics of the whole network and the features of each node in this network. The former includes measures such as average path length, diameter, number of edges etc. (for more details see Jackson, 2008), while the latter can help us find the nodes that play an important role in the system.

One of the most substantial characteristics of a node in a network is *centrality*. It can be interpreted in at least two ways for financial markets. First, as often used in the social sciences, it shows the importance of a node in terms of its connection with other nodes (see, for example, Jackson, 2008). The second interpretation is that centrality can represent the importance of a node in terms of systemic risk (e.g. Acemoglu *et al.*, 2015). For example, a more central node plays a greater role in shock propagation than a node with a lower centrality measure. Primarily, nodes that are identified as central in terms of these two interpretations coincide, which means that the most connected firms are also systemically the most important. However, if a network has both positive and negative edges, which might be the case for networks based on partial correlations, the interpretation of centrality is not clear. In this section we discuss some possible centrality measures from both perspectives.

There are different measures of centrality. One of the basic measures is *degree centrality*, which is calculated simply as a number of its adjacencies for an unweighted network.[2] A commonly used method for calculating the degree centrality of node i for a weighted graph is to sum the weights of each node connected with node i (Newman, 2004). However, for a network with positive and negative edges, where we should consider both interpretations of centrality, it is useful to distinguish degree centrality as follows:

$$\begin{aligned} DC_i^{net} &= \sum_{j=1}^{n} a_{ij}, \\ DC_i^{abs} &= \sum_{j=1}^{n} \left| a_{ij} \right|, \\ DC_i^{+} &= \sum_{j=1}^{n} \{ a_{ij} | a_{ij} > 0 \} \end{aligned} \tag{4}$$

where n is the number of nodes and a_{ij} is the ijth element of an adjacency matrix A.

In terms of systemic risk contribution the net degree centrality, DC_i^{net}, represents the net immediate effect on i's neighbours. However, this measure is uninformative in terms of connections with other agents as it does not distinguish whether node i has only positive connections or its connections have different signs. Absolute degree centrality, DC_i^{abs}, takes into account the absolute values of the strengths of relations, and therefore it is valid to measure the connectedness of a node with its adjacencies without considering the signs of these relations. Moreover, this provides the total effect on neighbours in the case of shock transmission. To measure only positive connections, we use DC_i^{+}, which allows us to capture the strength of the positive relations and shows the importance of a node in terms of the consequences of a negative shock on that node's neighbours.

[2] In some literature, *e.g.* Jackson (2008), normalized degree centrality is used for an unweighted network. That is, it is measured as the number of adjacencies divided by $n-1$, where n is the number of nodes in the graph. However, as the number of nodes does not change over time in our case, we do not use normalization.

To calculate centrality, one might also want to consider the number of immediate neighbors a node has. The sum of the absolute weights measures total involvement in the connectedness of the network but does not take into consideration the number of the edges of each node. To illustrate this problem let's consider an example illustrated in Figure 1. Let node 1 be connected only to node 2 with the weight of the connectedness $w_{12} = 7$ and node 3 has five neighbours and let the strength of the connectedness with each of them be equal to 1. According to equation (4), the degree centrality[3] of node 1 exceeds the degree centrality of node 3. However, node 3 is more central when looking at its total number of neighbours. Therefore, it is of importance to take into account both the sum of the weights and the number of neighbors when calculating node centrality.

Opsahl, Agneessens, Skvoretz (2010) proposed using a tuning parameter α when measuring centrality. This parameter determines the preference of the number of edges for a node over the sum of the weights of its edges. Formally, they use the following measure of degree centrality:

$$DC_i^{tune} = k_i^{1-\alpha} \times DC_i^{\alpha}. \tag{5}$$

Here k_i is the number of adjacencies of node i and DC_i is one of the degree centralities introduced above. It should be noted that equation (5) coincides with the equations in (4) with $\alpha = 1$, and $\alpha = 0$ gives the number of edges of node, k_i. In other words, DC_i^{tune} measures degree centrality giving more value to the weights of the node when α is close to one and providing more value to the number of edges as α approaches zero. See Table 1 for an example comparing DC and DC^{tune}.

Another measure of centrality is *eigenvector centrality,* which defines the centrality of a node based on the centrality of its neighbours. Let C^e be the centrality vector of a given network and $C^e(i)$ be the centrality of node i in this network. The idea of eigenvector centrality is that the centrality of a node is proportional to the centrality of its neighbours (Bonacich, 1987; Jackson, 2008). Formally, $\lambda C^e(i) = \sum_{j=1}^{n} w_{ij} C^e(j)$, where λ is some proportion factor. In matrix form it can be written as

$$\lambda C^e = A C^e \tag{6}$$

It is easy to see that this equation holds when λ is an eigenvalue of adjacency matrix A and C^e is its corresponding eigenvector. The standard approach is to look at the eigenvector associated with the maximum absolute eigenvalue of the adjacency matrix (for more details see Bonacich, 1987; Jackson, 2008).

In contrast to degree centrality, eigenvector centrality takes into account how influential

[3] As we do not use edges with negative weights in our example, the introduced degree centrality measures coincide.

the adjacencies of a node in the network are. In other words, a node is more central when the neighbours of that node are more central. Another advantage of eigenvector centrality is that it can be applied to networks with connections with different signs (Bonacich, 2007) such as in partial correlation networks. Moreover, in terms of systemic risk eigenvector centrality shows how far and to what extent a shock can propagate in the system (Anufriev and Panchenko, 2015). On the other hand, for a graph with weights with different signs it is possible to look at eigenvector centrality based on an adjacency matrix of absolute values of partial correlations. This kind of centrality will give us the total connections of node in terms of the absolute connections of its neighbours.

An important question for systemic risk is to find a quantitative measure which characterizes the stability of a system to external shocks. This measure can be derived with the help of network theory. Let e be an adverse shock experienced by firm i. Mathematically, this shock can be written as a vector with non-zero i-th element and with zeros for the rest. First, the shock can affect i's immediate neighbours. Following Anufriev and Panchenko (2015), we refer to this as a first-order effect, which can be measured as $A \cdot e$. We should note that the first-order effect of node i is exactly the net degree centrality of this node, DC_i^{net}, if we assume a unit size shock. Next, the effect on the neighbours of i's neighbours can be expressed as $A^2 \cdot e$. This is called a second-order effect. Following this idea we can derive a k-th-order effect. The total effect of the adverse unit shock e on the node i can be written as follows:

$$e + A \cdot e + A^2 \cdot e + A^3 \cdot e + \dots = \sum_{j=0}^{\infty} A^j e = (I - A)^{-1} e \tag{7}$$

where I is the identity matrix. If we denote $T = (I - A)^{-1}$, then the vector $T \cdot e$ shows the total effect of adverse shock e on all agents in the system. Summing up all the elements of vector $T \cdot e$, we can obtain the total effect on the system caused by the shock in one node.

It should be noted that equation (7) only holds under the assumption that all eigenvalues of adjacency matrix A are within the unit circle. However, the corollary of Gershgorin's theorem states that the eigenvalues of an adjacency matrix cannot exceed the maximum sum of the row elements in absolute terms (for details see Varga, 2000), which in our case is maximum absolute degree centrality. That is why in application in networks based on the GGM this assumption does not necessarily hold. Nevertheless, if some eigenvalues are out of the unit circle, then the series in (7) diverges. In terms of shock propagation, it means that the system is unstable in the sense that a shock to some nodes can lead to an enormous effect on the system. Hence, the eigenvalue of an adjacency matrix can also be used as the characteristic of a network: if there is an eigenvalue larger than one in absolute terms, then the network can be thought of as unstable.

It has been shown that *Bonacich centrality* is linked to the total effect matrix T (Anufriev and Panchenko, 2015). Indeed, the centrality measure proposed by Bonachich (1987), also known as beta-centrality, is given as:

$$C^B(\beta) = \sum_{j=1}^{\infty} \beta^{j-1} A^j \cdot 1_n = (I - \beta A)^{-1} A \cdot 1_n \tag{8}$$

where β is a parameter of transmission, which shows extent to which shocks transmit between vertices. For $\beta = 1$ Bonacich centrality becomes:

$$C^B(1) = A \cdot 1_n + A^2 \cdot 1_n + A^3 \cdot 1_n + ... = T \cdot 1_n - 1_n$$

which represents the total effect on the system caused by a unit idiosyncratic shock in each node separately. In other words, the Bonacich centrality of node i is the cumulative total effect on the system caused by a shock in this node minus the shock itself, that is the sum of the elements of vector $T \cdot e$ minus 1. Therefore, looking at the value of Bonacich centrality, we can decide how much a node is systemically important in terms of shock propagation.

The transmission parameter β reflects the diminishing order effect of a shock in the sense that only part of the shock transmits to its neighbours. Moreover, the assumption that all eigenvalues of the adjacency matrix are contained within the unit circle imposed in (7) is necessary to estimate the total effect of shocks, while Bonacich centrality can be calculated using $\beta < 1/\lambda$ sufficient for the convergence of the series (Bonacich, 2007).

We are also interested in looking at the characteristics of a network as a whole, such as the number of edges, sum of weights and average path length of the network. The number of edges and sum of weights in the network are self-explanatory names of graph measures. *The average path length* measures the average shortest path between nodes. It shows the average number of steps in shock propagation for the network. All three characteristics show the degree of connectedness in a network: the more connected the network, the less the average path length, the greater the number of edges and the sum of weights. In Section 7 we examine these characteristics over time to see in which periods our network of the stocks in MICEX was more or less connected.

Moreover, it is interesting to identify the periods when the system in general was more vulnerable to shocks. In order to do so we could make use of the network measures discussed in Section 3. As Bonacich centrality shows the systemic importance of a node, the average of all Bonacich centralities[4] of nodes represents how the market in general refers to systemic risk. The total number of edges and the number of negative edges increase during days of crisis because there are new connections made. Similarly, the sum of positive weights and

[4] The sum of Bonacich centralities across all stocks divided by the number of stocks.

the sum of the absolute values of weights increase when there is a crisis because the network becomes more connected with stronger ties. If the maximum absolute value of eigenvalues approaches one, as happens in a crisis, the network becomes more unstable. Finally, average path length, that is the average distance between the nodes of the network, and diameter, that is the longest distance between any two nodes in the network, both decrease when there is a crisis because the stocks follow each other much more closely. Hence all these network measures are related to the vulnerability of a system.

We derive the vulnerability index of a market by using the principal components analysis of the network measures. We call the first component obtained from the principal components analysis the *vulnerability index* of a market in the sense that it shows us how vulnerable the system is to idiosyncratic shocks due to its network structure: the greater the vulnerability index the more vulnerable the market. To distinguish the possibility that larger firms may cause larger falls, we also consider the weighted average of the Bonacich centralities with the capitalization of firms as the weights and call it the *weighted vulnerability index.* These measures help to compare the conditions of a market over time in terms of its sensitivity to negative shocks.

4 Data on the stocks in MICEX

We use daily stock returns to construct the network of interconnections between companies. We concentrate our attention on the major companies of the Russian Federation, which determine the tendency of economic development. These companies are included in the main indices of the Moscow Exchange such as MICEX, nominated in rubles, and RTS, nominated in dollars. Both indices consist of the 50 most liquid stocks of the largest Russian issuers from the main sectors of the economy. We use the stock prices in MICEX, obtained from the Moscow Stock Exchange. There are several firms that issued both common stocks and preferred stocks (e.g. Sberbank has common stocks traded with ticker SBER and preferred stocks with ticker SBERP); therefore we used only those with common stocks. In addition, Rosseti (RSTI) owns 80 per cent of the shares in FGC UES (FEES), which gives strong dependence between them; therefore we only used data from Rosseti for our analysis. From the selected list of firms we chose the number of series and data length considering that we wanted to use as many observations as possible with as many companies as possible. Our data sample spans the period from 1 December 2011 to 29 January 2016 and includes 35 firms, which form around 90 per cent of the market capitalization within the MICEX index. The list of companies with tickers and sectoral classifications is provided in Table 2.

While studying the data, we noticed that there are outliers in the stock returns. When we compared these outliers with the outliers of sectoral indices and the MICEX index, we noticed that one common large outlier falls on 3 March 2014, which is the date Russian markets experienced losses due to the discussions on the annexation of Crimea to the Russian Federation and the potential consequences.[5] The rest of the outliers in the stock returns were stock specific. Therefore, using the Hampel filter of Hampel *et al* (1986), we replaced the stock specific outliers with local medians.[6] Finally, we put back the return observations that belonged to 3 March, 2014 and included a dummy variable to the mean and variance equations in order to account for this outlier.

We also consider the possible existence of common factors. As mentioned by Barigozzi and Brownlees (2016), common unobservable factors may induce high correlations between returns. Given that partial correlation calculations may not eliminate these common factors, we may spuriously end up with a fully connected network. Therefore, we need to filter out a possible common factor from the return data before carrying out the network analysis. For simplicity we assume that all stock returns might be affected by one common unobservable factor.[7] This could be political background, index of a leading stock market, GDP, or some other factor.

In what follows, we explain our econometric approach to derive the correlation dynamics.

5 Econometric Models

In our paper we use the correlations obtained from the constant conditional correlations GARCH (CCC-GARCH) model of Bollerslev (1990) and the consistent dynamic conditional correlations GARCH (cDCC-GARCH) model of Aielli (2008). We denote the number of return series by n, which is the notation we used for the number of nodes in Section 3. We construct our equations as follows.

[5] http://money.cnn.com/2014/03/03/investing/russia-markets-ruble/

[6] For the Hampel filter, we chose a one-month window (local median is calculated from this one-month window) and a threshold value of 5, which makes the probability of observing an outlier very small. Hence, we only filtered away very large outliers.

[7] We could have considered multiple factors. In particular we could have used sector-specific factors. However, in the data we use some sectors that have only one or two companies: there is only one company in the transport sector, two companies in the telecommunication and CD&S sectors. In these cases the unobserved sector-specific factors would be difficult to capture, if at all. Also, with sector-specific factors, interconnection with companies from different sectors will lose their interpretation. Second, if we include a lot of common factors, then we end up with a highly sparse network. Finally, the sector-specific factors add many additional parameters to estimate in step 1b of Section 6, which brings about some numerical optimization issues. We used one factor, which is a combination of external factors that affect all sectors. We analyze the factor estimate and its relation to external factors in Section 8.4. This parsimonious approach helps to capture the unobserved factor, but still avoids to some extent the danger of ending up with a highly sparse network.

5.1 Conditional Mean

We define r_t to be an nx1 vector of return series, and so then the return equation is given by:

$$\begin{aligned} r_t &= \mu_1 + \mu_2 Out_t + \beta r_{t-1} + c f_t + \varepsilon_t \\ f_t &= \rho f_{t-1} + \omega_t \\ \begin{pmatrix} \varepsilon_t \\ \omega_t \end{pmatrix} &\backsim N\left(0_k, \begin{bmatrix} H_t & 0 \\ 0 & \Sigma \end{bmatrix}\right) \end{aligned} \tag{9}$$

where β is an nxn matrix, μ_1, μ_2 and c are nx1 vectors of parameters and ρ is a scalar parameter, Out_t is a dummy that stands for the outliers and f_t is an unobserved factor. ε_t and ω_t are assumed to be orthogonal, hence we have a linear state space form. This is a VAR(1) model that considers a dummy variable for outliers and also includes an unobserved latent variable. We assume that there is only one common factor for simplicity.

5.2 Conditional Variance

The conditional variance of the errors ε_t in the conditional mean equation is given by H_t such that:

$$\begin{gathered} \varepsilon_t = H_t^{1/2} v_t \\ H_t = D_t R_t D_t \\ D_t = diag(h_{1t}^{1/2}, h_{2t}^{1/2}, ..., h_{nt}^{1/2}) \\ h_{t+1} = W_1 + W_2 Out_{t+1} + A\varepsilon_t^{(2)} + B h_t \end{gathered} \tag{10}$$

where the conditional variance H_t is decomposed into a diagonal matrix of conditional volatilities h_t and correlation matrix R_t. W_1 and W_2 are nx1 vectors, A and B are diagonal nxn matrices of parameters. $\varepsilon_t^{(2)}$ is a vector of squared errors from equation (9). Hence for each series i, the corresponding volatility equation is:

$$h_{i,t+1} = w_{1i} + w_{2i} Out_{t+1} + a_i \varepsilon_{i,t}^{(2)} + b_i h_{i,t}$$

The conditional variances, $h_{i,t}$ are positive as long as parameters $w_{1i} > 0$, $w_{2i} \geqslant 0$, $a_i \geqslant 0$ and $b_i \geqslant 0$ for all i, which is a sufficiency condition. On the other hand, $h_{i,t}$ are stationary when $a_i + b_i < 1$.

5.3 Conditional Correlation

We consider two conditional correlation models, depending on how the conditional correlation matrix R_t is constructed. The first and simplest one is the Constant Conditional Correlation GARCH model of Bollerslev (1990) where the correlation matrix is constant overtime, $i.e$ $R_t = R$. This constant correlation matrix tells us the correlation between the returns over all the sample periods and hence will help us to have a general look at the network connections between firms and sectors.

The second specification we consider is the cDCC-GARCH model of Aielli (2008) which extends the correlation equation of the CCC-GARCH model by defining correlation dynamics as follows:

$$\begin{aligned} R_t &= P_t Q_t P_t \qquad (11) \\ P_t &= diag(Q_t)^{-1/2} \\ Q_{t+1} &= (1-\delta_1-\delta_2)\overline{\mathbf{Q}} + \delta_1 \nu_t^* \nu_t^{*\prime} + \delta_2 Q_t \\ \nu_t^* &= diag(Q_t)^{1/2} \nu_t. \\ \nu_t &= D_t^{-1} \varepsilon_t \end{aligned}$$

where Q_t is an nxn covariance matrix from which the correlations are derived, $\overline{\mathbf{Q}}$ is replaced in the estimation by S, the sample covariance of the ν_t^*. This is referred to as the *correlation targeting* approach (Engle, 2009) and it significantly reduces the number of parameters to be estimated. δ_1 and δ_2 are non-negative scalar parameters which satisfy $\delta_1 + \delta_2 < 1$. Using the correlation estimates of the cDCC-GARCH model, we can derive the correlations between firms and sectors at each period, and therefore we can view the network connections on a particular date: for example before and after a shock that affected the MICEX index.

6 Estimation

Given that we consider many series and therefore we have many parameters to estimate, we estimate our models in three steps: first mean equation parameters, then volatility parameters and then correlation parameters. In this way, we obtain Gaussian three-step estimators, which are consistent and asymptotically normal (See Engle and Shephard, 2001). The Monte Carlo simulations in Carnero and Eratalay (2014) show that they behave well in small samples.

Step 1. We first estimate the mean equation parameters $\Psi = [\Psi_1, \Psi_2]$ in two small steps:

Step 1a: we first estimate a VAR(1) model ignoring the latent variable and assuming homoscedasticity. Hence if we define:

$$
\begin{aligned}
X &= [\vec{1}, Out_t, r_{t-1}] \\
y &= r_t
\end{aligned}
$$

where X is a $(T-1)$x3 matrix, and y is a $(T-1)$x1 vector, then the matrix of coefficients $\Psi_1 = [\mu_1, \mu_2, \beta]$ and residuals can be obtained by:

$$
\begin{aligned}
\hat{\Psi}_1 &= [X'X]^{-1}X'y \\
\hat{\varepsilon}_t^* &= y - X\hat{\Psi}
\end{aligned}
$$

This is equivalent to a maximum likelihood estimation under the assumption of homoscedasticity. The fact that the latent variable is in the error term causes serial correlation in the error, which results in inefficiency but not inconsistency of the estimator.

Step 1b: assuming homoscedastic errors, we then estimate the parameters $\Psi_2 = [c, p, H, \Sigma]$ of the mean equation:

$$
\begin{aligned}
\hat{\varepsilon}_t^* &= cf_t + \varepsilon_t \\
f_t &= \rho f_{t-1} + \omega_t \\
\begin{pmatrix} \varepsilon_t \\ \omega_t \end{pmatrix} &\backsim N\left(0_n, \begin{bmatrix} H & 0 \\ 0 & \Sigma \end{bmatrix}\right)
\end{aligned}
$$

These equations are in a linear state space form, and the errors ε_t and ω_t are orthogonal. Hence we can apply a Kalman filter[8] to the residuals and construct the prediction error decomposition form of the loglikelihood:

$$
L(\Psi_2|\hat{\Psi}_1) = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=2}^{T}\log|F_t| - \frac{1}{2}\sum_{t=2}^{T} e_t' F_t^{-1} e_t
$$

where e_t is the prediction error and F_t is the prediction error variance.

Step 2. We take the prediction errors as the residuals to enter the variance equation. Hence the volatility equation for each series i is given by:

$$
h_{i,t+1} = w_{1i} + w_{2i}Out_{t+1} + a_i\hat{e}_{i,t}^{(2)} + b_i h_{i,t}
$$

Given that there are no volatility spillovers, we can estimate the conditional variance parameters $\Phi_i = \{w_{1i,}w_{2i,}a_i, b_i\}$ for each return series i univariately by maximizing the

[8]The algorithm of the Kalman filter we used is given in Appendix I.

following loglikelihood with respect to Φ_i:

$$L(\Phi_i|\hat{\Psi}) = -\frac{T}{2}\log(2\pi) - \sum_{t=2}^{T}\log h_{i,t} - \frac{1}{2}\sum_{t=2}^{T}\nu_{i,t}^2$$

where $v_{i,t} = \hat{e}_{i,t}/\sqrt{h_{i,t}}$ are the standardized errors corresponding to series i.

Step 3. We estimate the correlation dynamics following the composite likelihood method discussed in Engle, Sheppard and Shephard (2008). This is equivalent to a classical maximum likelihood method for estimating the correlations of a CCC-GARCH model. However when estimating the correlation parameters of the DCC and cDCC-GARCH models with a high number of series, Engle and Sheppard (2001) and later Engle, Sheppard and Shephard (2008) noted that attenuation biases are observed in the δ parameters of equation (11), resulting in smoother correlation estimates. For a very high number of series, the estimated correlations are close to being constant and equal to the long-run matrix. This might lead researchers to assume that the conditional correlations in the data are constant over time. The composite likelihood method solves this problem by choosing small subsamples, evaluating the loglikelihood of these subsamples and taking an average over these loglikelihoods.[9]

Taking $\hat{v}_{i,t} = \hat{e}_{i,t}/\sqrt{\hat{h}_{i,t}}$ from the first two steps, we can estimate the correlation matrix of a CCC-GARCH model by:

$$\hat{R} = corr(\hat{v}_t) = \frac{\sum \hat{v}_{i,t}\hat{v}_{j,t}}{\sqrt{\sum \hat{v}_{i,t}^2 \sum \hat{v}_{j,t}^2}} \tag{12}$$

For the estimation of the cDCC-GARCH model, we take $\hat{\Psi}$ and $\hat{\Phi}$ from the first two steps and we choose subsamples from n series. These subsamples can be chosen as all subsequent series such as {{1,2},{2,3},...{$n-1.n$}, or all possible bivariate combinations. It is also possible to choose trivariate subsamples as well. In our paper, we use all possible bivariate combinations. Let us denote the correlation parameters with $\Delta = \{\delta_1, \delta_2\}$. We allow for different dynamics for the correlations: the correlations evolve between firms of the same sector using parameter vector Δ_1 and between firms of different sectors with Δ_2. Hence, if the chosen subsample comes from the same sector, the corresponding correlation parameter vector is Δ_1, if not, then it is Δ_2.

Finally, for each of the subsamples we choose, we construct the loglikelihood:

$$l_s = -\frac{1}{2}\sum_{t=2}^{T}\left(\log|R_t| + \widehat{\nu}_t' R_t^{-1}\widehat{\nu}_t\right) \tag{13}$$

[9]Hafner and Reznikova (2010) suggest, as another approach, the use of shrinkage methods to solve this problem.

and we maximize the following loglikelihood with respect to $\Delta = [\Delta_1, \Delta_2]$:

$$L(\Delta|\hat{\Psi}, \hat{\Phi}) = \frac{1}{N} \sum l_s$$

where N is the number of subsamples.

After obtaining $\hat{\Delta}$, a forward recursion based on equation (11) using all series would provide the conditional correlation estimates, $\hat{R}_t$.

Although this three step procedure is not efficient, it still provides consistent and asymptotically normal estimators. (See Engle and Shepard, 2001, Engle, Sheppard, Shephard, 2008).

7 Empirical Part

In this section we apply the network theory approach we described in Section 3 to study the connectedness between major firms in Russia. First, we assume that the connections did not change over time, and we analyze the overall interconnectedness in the static system. Later, we let these connections evolve so that we can comment on the changes in the characteristics of the network over time.

7.1 Constant correlations

The constant correlation matrix $\hat{R}$ is estimated as correlations between standardized residuals in the CCC-GARCH model with the help of equation (12). Using equation (2) we obtain an estimation of the constant partial correlation matrix. Figure 2 displays histogram of ordinary correlations and partial correlation coefficients. It can be seen that although there are no negative correlations, some partial correlations can be negative. However the majority of the partial correlations are positive.

In order to map a sparse network of interconnectedness we use the Fisher's Z transformation of partial correlations and its 10% "significance level" as a threshold value. However we do not interpret it as a test for the statistical significance of partial correlations due to a possible multiple testing problem. Instead, a 10% significance level is employed as one of the possible threshold values to achieve sparsity. The qualitative results are robust to the other threshold values.

The network based on the GGM is depicted in Figure 3. Positive relationships between firms are indicated by solid lines while negative relationships are denoted by red dashed lines. Thicker lines represent stronger relationships between nodes. Nodes are coloured according to the sectors they belong to. Moreover we depict state-owned and regulated firms[10] using square nodes and private ones using circle nodes.

The graph in Figure 3 is crowded with links, so it is complicated to make any conclusions visually based on it. However we can increase the threshold value to obtain sparser network. For example, Figure 4 shows the graph constructed with a cutoff point of 0.09, where we can see strong connectedness within some sectors such as Oil&Gas and Power sectors. Moreover, one can see clusters of some firms from the Oil&Gas sector and Metal&Mining sector, although there are also some negative links between these two sectors.

Interestingly that the negative connections in Figures 3 and 4 are not between firms from one sector, where companies typically compete with each other, but, in contrast, they are formed between firms from different sectors. In particular, the strongest negative connections, as can be seen in Figure 4, are mainly between firms from the Oil&Gas and Metal&Mining sectors. In other words, the returns of some pair of firms from the Oil&Gas and Metal&Mining sectors counter-move with each other.

In Table 3 we summarize some network characteristics aggregated by sectors. As one can see, among the 35 largest companies in Russia, 8 firms belong to the Oil&Gas sector and 7 - to the Metal&Mining sector. Moreover, the Oil&Gas sector takes more than half of the capitalization among the considered firms, while Metal&Mining has around 12 per cent, which is outperformed by the Financial sector. Also more than half of the considered firms from the Oil&Gas, Power and Financial sectors are state-owned or regulated firms.

To compare the strength of intra sector connectedness, we calculate the number of edges and the sum of weights within each sector and normalize them on the basis of the number potential connectedness. The results suggest that there is strong connectedness within the Power and Financial sectors although they consist of only 3 firms. In terms of both the presence of the links and their strength the Oil&Gas sector outperforms Metal&Mining and Consumer Goods and Services (CGS) sectors (the second and the third largest sectors considered here respectively). In general, one can anticipate the strong connectedness within sectors for the estimated network of partial correlations. Firms from one sector are often influenced by sector-specific external shocks, hence their returns co-move in the stock exchange. For example, connectedness within the Oil&Gas sector can be explained by the dependence of all firms in this sector on the price of oil.

It is of interest to identify central players both in terms of their connection with other firms and shock propagation in the case of a constant correlation model. We use the cen-

[10] By state-owned and regulated firms we denote those that belong to the composite Moscow Exchange (MOEX) State-Owned Companies Index (SCI) and the MOEX Regulated Companies Index (RCI), i.e. those firms with the state in the shareholder structure and firms that are additionally regulated by Russian Ministries. In our dataset there are 12 state-owned and regulated firms.

trality measures discussed in Section 3. In Table 4 centrality measures are provided for the top twelve companies ordered according to Bonacich centrality (C^B), which represents the top systemic contributors. There k is the number of direct neighbours of a company; DC^{net}, DC^{abs}, DC^{+} are the degree centralities from equation (4). We also calculate eigenvector centrality, EC, to show how central firms are in terms of their neighbours' centralities. In order to compare different measures of connectedness we also use the degree centrality (DC^{tune}) measure suggested by Opsahl, Agneessens, Skvoretz (2010) with a tuning parameter $\alpha = 0.5$[11] and eigenvector centrality based on the adjacency matrix of absolute weights between nodes, EC^{abs}. We normalize both eigenvector centralities setting the largest component of each to 1 and sort the whole table in descending order of Bonacich centrality. The ranking order according to each measure is provided in parentheses on the right side of each value.

First of all, one can see that among the selected top twelve systemic contributors, there are 6 companies from the Oil&Gas sector (out of 8), 3 firms from the Metal&Mining sector (out of 7) and 2 (out of 3) firms from the Financial sector. This suggests that these sectors play a crucial role in systemic risk propagation. The importance of the first two sectors is not surprising for such resource dependent economy as Russia. While Oil&Gas companies might show a central position given their large capitalizations, firms from the Metal&Mining sector play a similar role as systemic risk contributors even though they have less capitalization. Moreover, the central position of firms from the Financial sector can be explained by their role as capital redistributors in the economy. The importance of the banking sector was also indicated for the Australian market in Anufriev and Panchenko (2015).

Moreover, Table 4 shows that the most central firms in the Russian Stock Market in terms of connection with others are Lukoil (LKOH), Sberbank (SBER) and Gazprom (GAZP). In terms of systemic importance Sberbank gave its place in the top 3 to NLMK Group (NLMK). Not suprisingly that the top firms in terms of connectedness are ones of the largest companies in the Russian stock market. However, among the top central firms in terms of systemic contribution, NLMK Group is only medium size company according to its market capitalization.

Another interesting fact is that the top 5 central firms according to eigenvector centrality are firms from the Oil&Gas sector. This emphasizes again that this sector is highly interconnected, and therefore these firms show a more central position also because of their central neighbours.

It is well known that state firms play one of the crucial roles in the Russian Stock Market. There are 12 such state-owned and regulated firms among the 35 considered here with a

[11] We could also use different values of α, but in order to show the difference between other centrality measures we use $\alpha = 0.5$ setting equal weights on the importance of edges and the sum of weights.

trading volume of more than 50 percent in the whole Moscow Stock Exchange. Therefore, it is not surprising to see Gazprom and Sberbank, which are state-owned firms and the largest in their industries (O&G and Financial sector respectively), among the top 3 interconnected firms. Interestingly, Lukoil, the largest private oil company, outperforms the second largest state-owned oil firm, Rosneft (ROSN) in terms of systemic importance. In general, among the top twelve systemic contributors there are 5 state-owned or regulated firms with a total capitalization of 46 per cent among the considered firms.

7.2 Dynamic correlations

The CCC-GARCH model gives us a constant network of connections in the Russian Stock Market. It is well known that Russia faced a number of problems during 2014, such as the devaluation of the ruble and trade sanctions imposed by the European Union and the Russian Federation. It can be said that 2014 was a year of financial and economic distress for Russia. During this period some of the firms suffered more than others due to, for example, stronger sensitivity to fluctuations in exchange rate and oil prices. Therefore, it would be a strong assumption to suggest that correlations between stock returns remained the same throughout the period. Hence, we are interested in examining how the connectedness between stocks changed over time, especially during the crisis. To do that we use the cDCC-GARCH model to obtain dynamic correlation matrix $\hat{R}_t$, which we use to calculate partial correlation matrix at each time t.

The methodology remains the same as in the constant correlation case except that we can now look at changes in the characteristics of the networks. In Figure 5 we present changes in the number of edges and the average path length, and in Figure 6 the sum of positive weights and their absolute values that we discussed in Section 3. All three characteristics vary over time and the number of edges and the sum of their weights increases in 2014, while the average path length declines in that year. Moreover, in Figure 6 one can see that the sum of absolute weights increases more than the sum of positive weights. These results are in line with the stylized fact that during the crisis the connectedness in the market strengthens and becomes polarized. Similar results were emphasized by Diebold and Yilmaz (2014) for the U.S. stock market in the period of the financial crisis 2007-2008.

In order to properly calculate the Bonacich centrality measure for each firm, we first have to look at the eigenvalues of adjacency matrices. In Figure 7 we present the maximum absolute eigenvalues of adjacency matrices over time. As we can see the assumption that all eigenvalues lie inside the unit circle is not satisfied throughout the period, and so we use $\beta = 0.9$ in equation (8) to calculate the Bonacich centrality measure such that the condition $\beta < 1/\lambda$ is satisfied. On top of that, one can think of the eigenvalue as one of the possible qualitative characteristics of a network. Indeed, under the assumption of a perfect propagation mechanism (shocks necessarily propagate through the obtained links), the cases where eigenvalues are larger than 1 correspond to an unstable system, that is convergence of the series in equation (8) fails, meaning that a negative shock experienced by a firm can lead to the whole system falling. Therefore, the crossing of the unit border can be interpreted as a qualitative change in the system. In fact, such a qualitative change of the obtained system can be seen at the end of 2014 in Figure 7 after the time when the exchange rate regime of the ruble was changed.

The dynamic characteristics of the network based on Bonacich centrality can be obtained by averaging this measure of each firm or weighting it by firm's capitalization. These measures, depicted in Figure 8, represent how the market in general refers to systemic risk, i.e. how sensitive it is to negative shocks. As one can see the largest value is reached in December of 2014 indicating that the Russian Stock Market was considerably sensitive to the external shocks at that time. Although both measures show similar dynamics, the weighted average characteristic is more volatile, in other words it is more sensitive to negative shocks, than the average of Bonacich centralities.

In addition, it is of interest to look at the central firms before, during and after the crisis. To do so, we choose three dates at the end of 2013, 2014 and 2015 for each of these periods respectively. Figures 9 – 11 represent the network on each of these days and Tables 5 – 7 provide centrality measures on those dates before, during and after the crisis the for top twelve systemic contributors in terms of Bonacich centrality.

First of all, it should be noted that the values of all centrality measures (except eigenvector centrality as it gives only a ranking rather than absolute values) increased at the time of the crisis. This shows again that during the period of distress, links strengthen and the network becomes more connected. Moreover, the system became more fragile during the crisis because systemic risk contribution of each firm in terms of Bonacich centrality also increased.

Specifically in terms of system risk contribution one can see that during and after the crisis the main contributors are the firms from the Oil&Gas sector (according to the ranking of the Bonacich centrality), while before the crisis they were Sberbank and two firms from the Metal&Mining sector (Surgutneftegas, SNGS, and NLMK Group, NLMK). Interestingly, Rosneft, the second largest state-owned oil company, was not in the top twelve list before the crisis, but then increased its systemic contribution during and after the crisis. In terms of connection with other companies, Sberbank and Lukoil are among the most central firms in all time slices.

8 Further discussion

8.1 Deriving the vulnerability index

Using the measures of the network discussed in Section 3 and listed in Table 8, we conduct a principal components analysis. Afterwards, we look at the first principal component. We rescale the first principal component to the range 0-100 in order to obtain vulnerability indices.[12] The first vulnerability index we consider uses the average of Bonacich centralities and other network measures while the second uses the weighted average of Bonacich centralities using the market valuations of the stocks as weights. The former is depicted in Figure 12 and shows a similar dynamic to the latter given in Figure 14.

Table 8 provides the coefficients of the analysis corresponding to the first principal component for each index. For both vulnerability indices, only the first eigenvalue was larger than one; therefore only one principal component was retained. While the vulnerability indices are mainly influenced by the number of edges, the sum of positive weights, the sum of absolute values of weights and the average path length, the influence of Bonacich centralities can not be ignored. In the case of the weighted vulnerability index, the effect of Bonacich centralities is slightly higher. It is not surprising that the average path length and diameter measures have negative coefficients, as they are expected to decrease during crisis periods. We can see that the first principal component explains 78-79% of total variance, which means that the vulnerability indices we consider summarize the information contained in these network measures by almost 80%. Indeed, as one can see from Figures 12 and 14, the vulnerability indices emphasize the crisis period: they start to increase in the second part of 2014 and reach a peak at the beginning of 2015 showing that the Russian market was more vulnerable during that period.

8.2 In relation to major credit rating agencies

In order to justify our vulnerability measures empirically, we look at the government debt credit ratings scores given by major credit rating agencies, namely, Standard & Poor's, Moody's and Fitch assessing the credibility of the Russian economy in our data period from 1 December 2011 to 29 January 2016.[13] In Table 9, we present the time series data of the credit ratings and outlooks and the rating scales we create to which they correspond. Moreover, we give the vulnerability and weighted vulnerability indices calculated from the principal

[12] The formula for rescaling is: $index_{new} = 100\text{x}\frac{(index_{old} - \min(index_{old}))}{(\max(index_{old}) - \min(index_{old}))}$. There was the need for rescaling because some of the predicted values of the first principal component were negative and this would make it difficult to interpret.

[13] The data source is: http://www.tradingeconomics.com/russia/rating

components analysis. The rating scale is calculated setting the worst possible credit score as 0 points and best as 24 points and allowing for increments of 1 point for each category. The rating scale is then adjusted for outlook; i.e. negative or positive, for which we gave half points, and if there is also "watch" assigned to the outlook (such as a negative watch) we gave a quarter points. Hence if the credit score is BBB, it corresponds to a rating scale of 16, if the score is BBB with an outlook that is negative then the rating scale with outlook is 15.50. If the score is BBB with an outlook that is a negative watch, then the rating scale with outlook becomes 15.25.

The correlation of the rating scale with outlook and the vulnerability index is -0.695, and with the weighted vulnerability index it is -0.703, which are both statistically significant at 1%. In Figure 13, we can see the comovement of the rating scale with outlook and the vulnerability indices. It is interesting to note that at least in two cases, the credit rating institutions are responding late when decreasing the ratings. From 21.03.2014 to 28.03.2014, the rating scale with outlook increases while the vulnerability indices increase. However from 28.03.2014 to 25.04.2014 the rating scale with outlook decreases while the vulnerability indices also decrease. A similar case can be observed between the dates 25.04.2014 and 17.10.2014.

8.3 In relation to ACRA FSI and RTSVX

We can also compare our vulnerability indices with other indices that indicate the stability of the Russian market. One of these indices is the Russian Volatility Index (RTSVX). Similar to VIX it measures stock market expectations of volatility. The volatility index rises during a time of distress reflecting the investors' fear about the market, and therefore RTSVX can be used as a "fear gauge" about the Russian market.

At the end of 2016 the Analytical Credit Rating Agency introduced a new index of the financial stress of the Russian Federation, called the ACRA Financial Stress Index (ACRA FSI).[14] This index evaluates the likelihood of financial crisis in Russia based on the concepts of systemic risk also using principal components analysis. However, contrary to our approach, the ACRA index does not consider the structure of the relationship between institutions. Instead, it measures the systemic vulnerability based on 12 external factors such as different market prices, interest rates, and currency exchange rates (for details of the methodology see ACRA, 2016).

In Figure 14 we provide both indices and the weighted vulnerability index and in Table 10 we report the correlations between the ACRA index, RTSVX index and different variables

[14] Analytical Credit Rating Agency (2016). Principles of Calculating the Financial Stress Index for the Russian Federation. https://www.acra-ratings.com/documents/129.

obtained in our work. The correlation of the sum of the absolute values of weights with the ACRA and RTSVX are the highest at 0.8225 and 0.5684, respectively. In the case of the ACRA index, the lowest correlation is with the average of Bonacich centralities and in the case of the RTSVX index, the lowest correlation is with the diameter measure. The vulnerability indices are correlated with the ACRA index by about 0.76 and with RTSVX by about 0.51. All the correlations in the table are statistically significant at 1%.

The result that the ACRA and RTSVX indices correlate more with the connectedness measures but not so much with the centrality measures is related to the fact that ACRA and RTSVX do not consider the structure of the interconnections between agents, although this can play a crucial role in systemic risk propagation. By taking into account different external factors, these indices measure how the economy in general (as one representative agent) reacts to changes in them. However, different institutions can react in different ways to the same news, and hence, it can lead to changes in the structure of the interconnections. Therefore, ACRA FSI, RTSVX and also the number of edges or average path length can be indicators of stress periods measuring the changes in the connectedness of the system. On the other hand, if one is interested in the sensitivity of the economy to systemic risk, it is worth looking at the structure of interrelations which is the approach using the vulnerability indices we propose.

8.4 About the unobservable factor

In this section we also look back to our model assumption that there is an unobservable factor affecting all the returns. We obtained the vector of the factor by applying the Kalman smoother based on the estimated model.[15]

In our model, we assumed that this factor is unobservable. Therefore, it could be any index or return of any market or perhaps a mixture of several of them. Keeping this in mind, we perform a canonical correlation analysis, where the first set of variables is only the factor estimate, while the second set of variables consists of returns and squared returns (in rubles) of various markets and the VIX index and their lags. The series we consider are the SP500 for the US and its implied volatility VIX, Brent oil for oil prices, USD/RUB for exchange rate market, the MICEX index for the Russian Stock Market, the HSI for Chinese Stock Market and Morgan Stanley Composite indices for emerging markets (MSCIEM) and for the world markets (MSCIW). Our reason for applying a canonical correlation analysis is to find the linear combination of the variables in the second set of variables that is most correlated with the factor estimate.

[15] Appendix I provides the equations adopted from Durbin and Koopman (2002) to obtain the Kalman smoothed estimate of the factor.

In Table 11, we provide the results of the canonical correlation analysis. The canonical correlation is given as 0.2883, which is statistically significant, although not very high. The coefficients of the variables that construct the canonical variable (the linear combination of the variables that is the most correlated with the smoothed factor estimate) are large and significant (with significance at 1%, 5% or 10% levels) for contemporary (no lags) MSCIEM returns, VIX, SP500 squared returns, USD/RUB squared returns and MSCIW squared returns. Moreover, the coefficients are significant for the first lags of USD/RUB returns, MICEX returns and MSCIEM squared returns and for the second lags of USD/RUB returns, VIX, SP500 squared returns and MSCIW squared returns. The correlations of the variables of the second set and the smoothed factor estimate are also given and in general they are in line with the coefficients.

As we can see, the smoothed factor estimate is related to external variables and their lags and the canonical correlation we obtain is only 0.2883. our large list of external factors are able to explain only some part of the unobserved factor. In practice this means that the unobserved factor we used is a combination of even more number of external factors. It could even be that some of these external factors are not easily measurable in numbers. For example political developments could be such an external factor. Therefore, the inclusion of an unobserved factor in the econometric model in Section 5 is justified.

8.5 Alternative simplified specifications

The idea of the GGM approach we use here is to derive a network of stocks using correlations of stock returns. One could simply take the correlation matrix of the returns for the analysis with constant correlations or use a rolling window estimation for dynamic correlations, but these approaches would be ignoring several points our model in Section 5 captures.

The data we use for analysis includes a very volatile period. If we would use equation 2 to extract correlations, we would be assuming that the conditional variances and covariances are constant over time. This would make sense if the data presented similar volatility behavior over the whole time period. However this is not the case. Constant conditional correlations GARCH accounts for the time varying volatilities and hence is more trustable than regular correlations in this analysis. Moreover, our approach takes into account any return spillovers (in the first lag) between stocks and an unobserved common factor. Capturing such dynamics in return and volatility equations could eliminate spurious relations which otherwise would seem like correlations between returns. Moreover our approach includes a dummy variable for the outlier that occurred on 3 March 2014. It is well known that the correlations between returns could be badly affected if that outlier is ignored.

To compare with the constant correlation case in Section 7.1, we looked at the simplified version of estimating the correlation matrix of stock returns. Qualitatively, the results did not change drastically in terms of the centrality measures of the estimated networks. The most central firms stayed the same while the order changed slightly for the less central firms.

Similarly to compare with the dynamic correlations case in Section 7.2, we used a rolling window estimation with a regular covariance matrix. We should note that this approach has several drawbacks. First of all, it is not trivial which window length should be used. A short window might lead to very volatile and possibly uninformative correlation estimates because of the small number of observations in each window. On the other hand, a large window length may result in overly smooth correlation dynamics and would also lead to a loss of information in the beginning and at the end of the sample. Second, for a usual choice of window length (even if it is 90 days) the effect of the outlier will be large when it is in the window span. Finally, given the small number of observations in each window, the effect of ignoring return and volatility dynamics would be larger. As expected, the results with the rolling window estimation method differed drastically and were less realistic compared to Section 7.2.

To save space, we did not include any tables or figures in this section. However, they are available upon request.

9 Conclusion

In this paper, we mapped the most liquid major firms in the Russian Stock Market bringing together the ideas from financial econometrics, Gaussian Graphical Model and network analysis. More specifically, we derived partial correlations from the correlation estimates of the constant conditional correlation (CCC) and the consistent dynamic conditional correlation (cDCC) GARCH models. Further using the Gaussian Graphical Model approach, we derived the undirected weighted network of connections between stocks for the cases of constant and dynamic correlation assumptions. Using different centrality measures we identified the most central firms in the Russian Stock Market in terms of their connection with others and systemic risk contributions. We found that the most connected firms are the private oil company Lukoil and the largest state-owned firms Gazprom and Sberbank. In terms of systemic risk contribution Sberbank gave up its place to NLMK Group. In addition, we examined the dynamics of some key network measures such as the number of edges in the graph, the sum of their weights and average path length. All considered measures capture the distress period of 2014-2015 in Russian economy.

On the other hand, using the characteristic measures of the estimated networks related to centrality and connectedness, we conducted a principal components analysis to come up with two measures of vulnerability in the system with the difference that the first uses the average of Bonacich centralities, and the second uses the weighted average of Bonacich centralities. For the weights, we considered the market capitalization of the stocks on each day. It turns out that the vulnerability indices discussed in our article represent comovement and high correlation with the government debt credit ratings reported by major credit rating agencies, namely Standard & Poor's, Moody's and Fitch and also with the Russian Volatility Index RTSVX and financial stress index ACRA FSI.

Our article can be extended in various ways. First of all, one could include more stocks of financial companies and banks in the data series. Then one can discuss the financial stability of the system. On the other hand, one could run vector autoregressions with vulnerability series and some external factors such as oil prices and exchange rates, to derive the impulse response functions. In this way, one could see how system vulnerability would react to shocks introduced to these series.

References

[1] Acemoglu, D., Ozdaglar, A., Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. American Economic Review 105, 564-608.

[2] Acemoglu, D., Carvahlo, V.N., Ozdaglar, A., Tahbaz-Salehi, A. (2012). The Network Origins of Aggregate Fluctuations. Econometrica, 80(5), 1977-2016.

[3] Adrian, T., Brunnermeier, M.K. (2016). CoVaR. American Economic Review,106(7), 1705-1741.

[4] Anufriev, M., Panchenko, V. (2015). Connecting the dots: Econometric methods for uncovering networks with an application to the Australian financial institutions. Journal of Banking and Finance, Vol. 61, S241-S255

[5] Aielli, G. P. (2008). Consistent estimation of large scale dynamic conditional correlations. Unpublished paper: Department of Economics, Statistics, Mathematics and Sociology, University of Messina. Working paper n. 47.

[6] Barigozzi, M., Brownlees, C. (2016). NETS: Network Estimation for Time Series. Working Paper. Barselona Graduate School of Economics.

[7] Bauwens, L., Laurent, S. and J.V.K. Rombouts (2006). Multivariate GARCH Models: A Survey. *Journal of Applied Econometrics*, 21, 79-109.

[8] Battiston, S., Puliga, M., Kaushik, R., Tasca, P. and Caldarelli, G. (2012). Debtrank: Too central to fail? financial networks, the fed and systemic risk. Scientific reports, 2, 541.

[9] Bonacich, P.(1987). Power and centrality: A family of measures. American Journal of Sociology, 1170-1182.

[10] Bonacich, P. (2007). Some unique properties of eigenvector centrality. Social Network, 555-564.

[11] Bollerslev, T. (1990). Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized ARCH Model. *The Review of Economics and Statistics*, 72, 498-505.

[12] Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics*, 31:307-327

[13] Borovkova, S., Lopuhaa, R. (2012). Spatial GARCH: A spatial approach to multivariate volatility modelling. Available at SSRN 2176781.

[14] Bougheas, S. and Kirman, A. (2015). Complex financial networks and systemic risk: A review. In *Complexity and Geographical Economics* (pp. 115-139). Springer, Cham.

[15] Brownlees, C., Engle, R. (2016). SRISKS: A Conditional Capital Shortfall Measure of Systemic Risk. Working Paper.

[16] Buhlmann.P., Van De Geer, S. (2011). Statistics for High-Dimensional Data: Methods, Theory and Applications. Springer.

[17] Carnero, A., Eratalay, M.H. (2014). Estimating VAR-MGARCH Models in Multiple Steps, *Studies in Nonlinear Dynamics and Econometrics,* Vol 18, 3.

[18] Diebold, F. X., Yilmaz, K. (2009), Measuring financial asset return and volatilty spillovers, with application to global equity markets, *The Economic Journal,* Vol. 119, Issue 534, 158-171.

[19] Diebold, F. X., Yilmaz, K. (2014), On the network topology of variance decompositions: Measuring the connectedness of financial firms, *Journal of Econometrics,* 182-1, 119-134.

[20] Durbin, J., Koopman, S.J., (2002), A simple and efficient simulation smoother for state space time series analysis. Biometrika Volume 89, No 3, pp 603 - 615

[21] Engle, R., N. Shephard and K. Sheppard (2008). Fitting and Testing Vast Dimensional Time-Varying Covariance Models. NYU Working Paper No. FIN-07-046.

[22] Engle, R. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business and Economic Statistics*, 20, 339-350.

[23] Engle, R., K. Sheppard (2001). Theoretical and Empirical Properties of Dynamic Conditional Correlation Multivariate GARCH. NBER Working Paper, No: W8554.

[24] Engle, R. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of Variance of United Kingdom Inflation, *Econometrica* 50:987-1008.

[25] Hafner C.M. and Reznikova, O. (2010) On the estimatiion of dynamic conditional correlation models, *Computational Statistics and Data Analysis,* forthcoming.

[26] Hampel, F. R., Ronchetti, E. M., Rousseeuw, P. J., Stahel, W. A. (1986). Robust Statistics: The Approach Based on Influence Functions. Wiley, New York.

[27] Hastie, T., Tibshirani, R., Friedman, J. (2009). The Elements of Statistical Learning. Volume 2. Springer.

[28] Iori, G. and Mantegna, R. N. (2018). Empirical analyses of networks in finance. In *Handbook of Computational Economics* (Vol. 4, pp. 637-685). Elsevier.

[29] Jackson, M.O. (2008). Social and Economic Networks. Princeton University Press.

[30] Krumsiek, J., Suhre, K., Illing, T., Theis, F., J., Adamski J. (2011). Gaussian graphical modeling reconstructs pathway reaction from high-throughput metabolomics data. BMC Systems Biology, 5-21

[31] Kunegis, J., Lommatzsch, A., Bauckhage, C. (2009). The Slashdot Zoo: Mining a Social Network with Negative Edges. Proceedings of the 18th international conference on World wide web, 741-750.

[32] Newman, M.E.J. (2004) Analysis of weighted networks. Physical Review E 70, 056131.

[33] Opsahl, T., Agneessens, F., Skvoretz, J. (2010). Node centrality in weighted networks: Generalizing degree and shortest paths. Social Networks 32, 245-251.

[34] Rice, J.,J., Tu, Y., Stolovitzky, G. (2005). Reconstructing biological networks using conditional correlation analysis. Bioinformatics 21, 765-773.

[35] Silvennoinen, A. and T. Teräsvirta (2009). Multivariate GARCH Models. In T. G. Andersen, R. A. Davis, J.-P. Kreiss and T. Mikosch, eds. *Handbook of Financial Time Series*. New York: Springer.

[36] Varga, R. S. (2000). Matrix Iterative Analysis. Springer Series in Computational Mathematics.

[37] Weiss, Y., Freeman, W. T. (1999). Correctness of Belief Propagation on Gaussian Graphical Models of Arbitrary Topology. Neural Computation, Vol. 13, No. 10, 2173-2200.

10 Appendix I

In this section we give the Kalman filter algorithm to construct the prediction error decomposition form of the loglikelihood function in *Step 1b* of the estimation in Section 6. The linear state space form equations are given as:

$$\begin{aligned} \hat{\varepsilon}_t^* &= cf_t + \varepsilon_t \\ f_t &= \rho f_{t-1} + \omega_t \\ \begin{pmatrix} \varepsilon_t \\ \omega_t \end{pmatrix} &\backsim N\left(0_n, \begin{bmatrix} H & 0 \\ 0 & \Sigma \end{bmatrix}\right) \end{aligned}$$

where the errors ε_t and ω_t are orthogonal. The Kalman filter algorithm is adopted from Durbin and Koopman (2002) as follows:

$$\begin{aligned} e_t &= \hat{\varepsilon}_t^* - cf_t \\ F_t &= c'P_t c + H \\ K_t &= \rho P_t c F_t^{-1} \\ L_t &= \rho - K_t c' \\ f_{t+1} &= \rho f_t + K_t e_t' \\ P_{t+1} &= \rho P_t L_t + \Sigma \end{aligned}$$

where $f_1 = 0$ and $P_1 = (1-\rho)^{-1}\Sigma$ are the initial values for the state vector f_t and its variance. e_t is the prediction error and F_t is the prediction error variance used in *Step 1b* of the estimation in Section 6 to construct the loglikelihood.

The Kalman smoother algorithm to obtain the smoothed estimates of the unobserved factor f_t is also adopted from Durbin and Koopman (2002). We first obtain the smoothed disturbance vector for ω_t on the basis of backwards recursion:

$$\begin{aligned} r_T &= 0 \\ r_{t-1} &= cF_t^{-1}e_t' + L_t r_t' \end{aligned}$$

and then smooth the unobserved factor f_t using a forward recursion:

$$\begin{aligned} f_1 &= \Sigma r_0 \\ f_t &= \rho f_{t-1} + \Sigma r_{t-1} \end{aligned}$$

which gives us the estimated unobserved factor used in Table 11 and Figure 14.

Figure 1: An example. The weight of the edge between node 1 and node 2 is equal to 7 while the weight of the other edges is equal to 1.

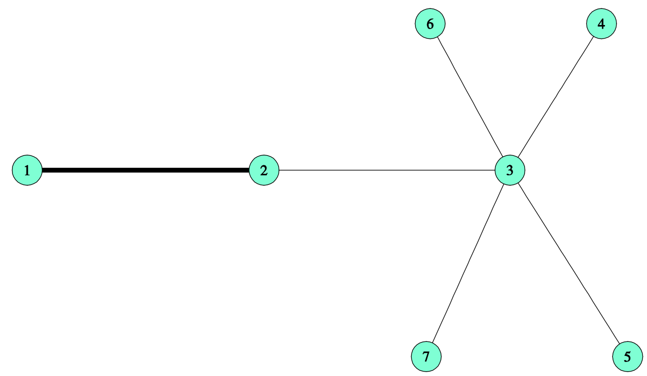

Figure 2: The histograms of ordinary correlations (left) and partial correlations (right) estimated using the CCC-GARCH model.

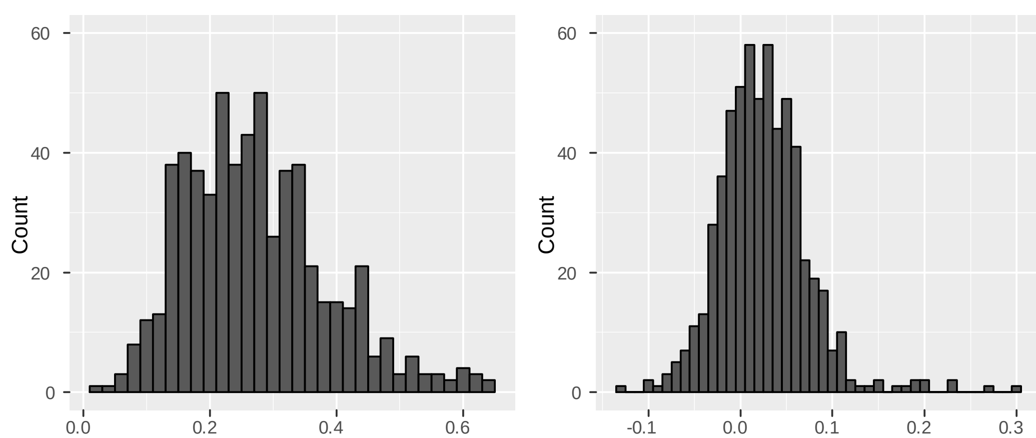

Figure 3: The constant correlation network of major Russian firms listed in MOEX. Nodes are colored according to the sectors and shaped according to the type of ownership. Solid lines between nodes denote positive conditional dependences between corresponding pairs while red dashed lines denote negative relations. The thicker the line the stronger the connection.

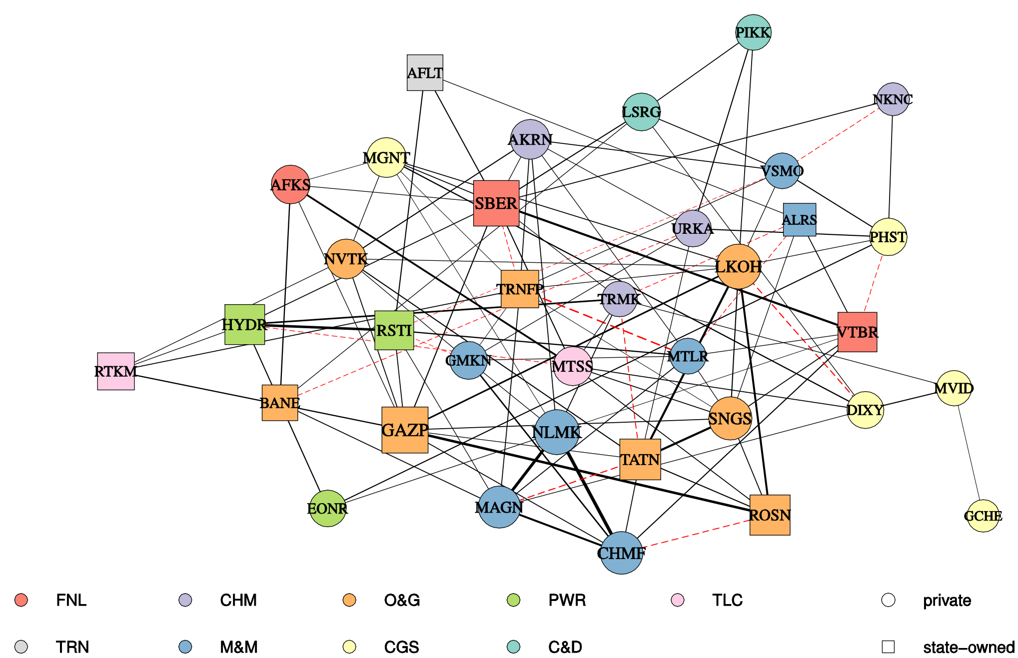

Figure 4: The constant correlation network with a threshold value equal to 0.09

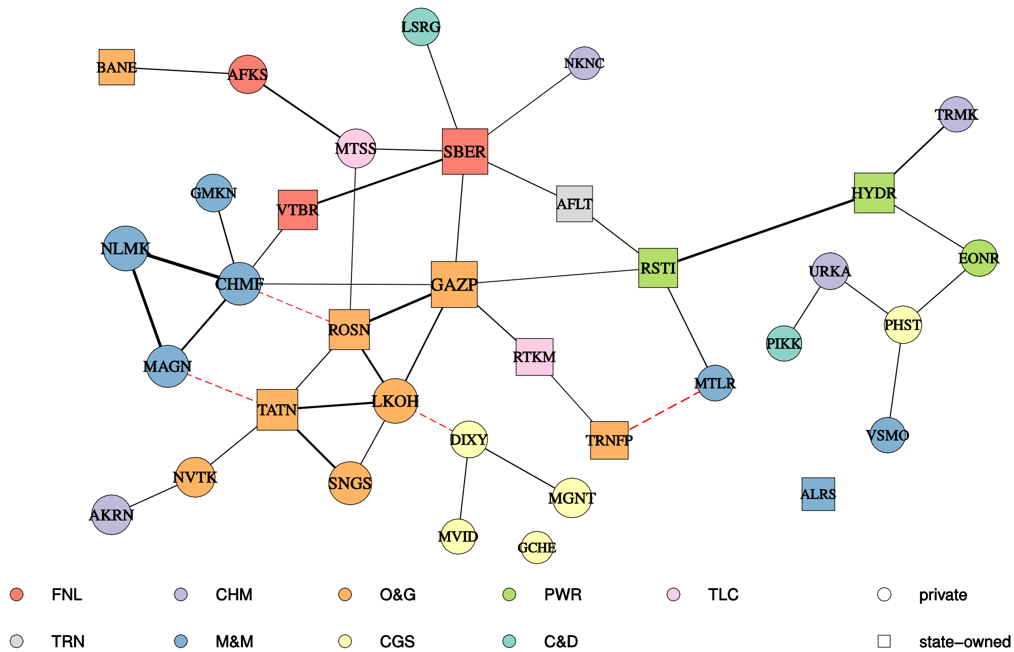

Figure 5: Dynamic of the normalized number of edges (left) and average path length (right) of the network

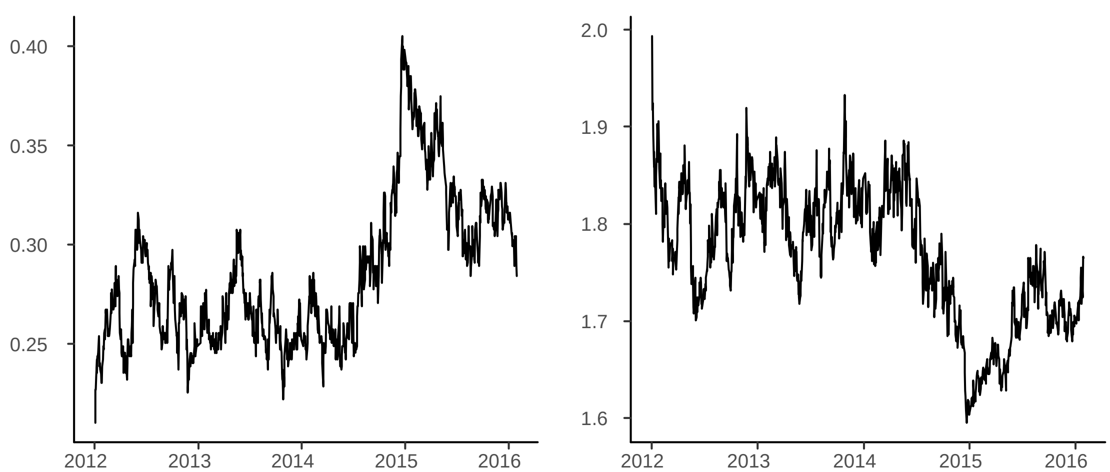

Figure 6: Dynamic of the sum of positive weights of the network (dashed line) and of the sum of absolute weights of the network (solid line)

Figure 7: Dynamics of the maximum absolute eigenvalues of adjacency matrices.

Figure 8: Dynamics of the average and weighted average of the Bonacich centralities

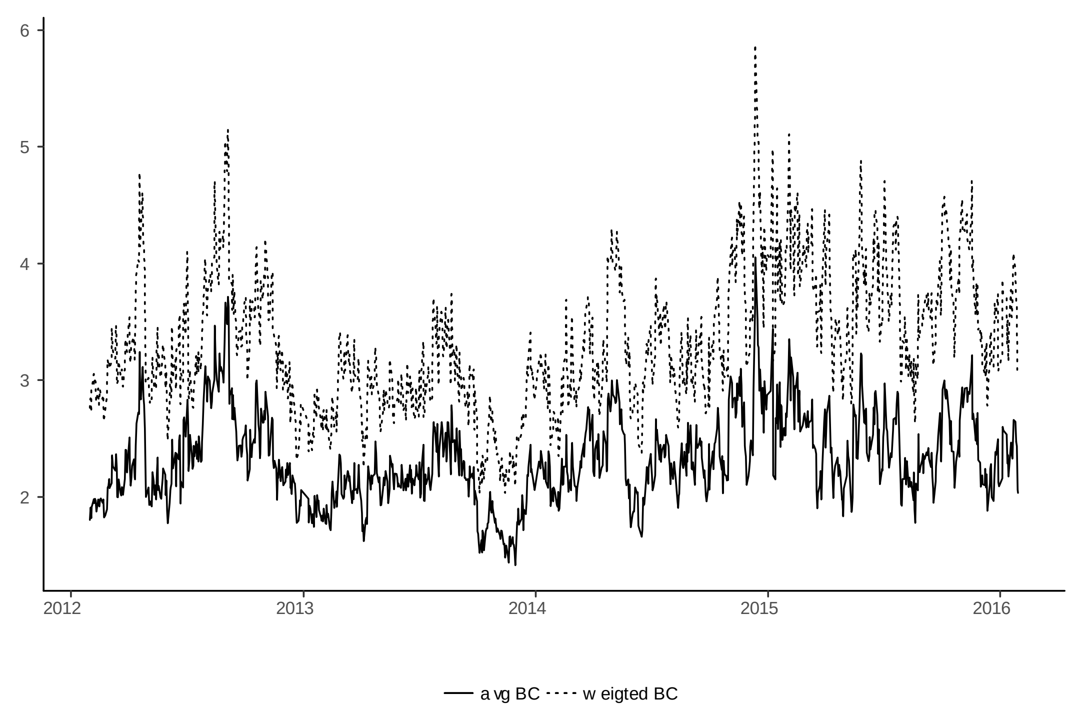

Figure 9: Dynamic correlation network, 30.12.2013

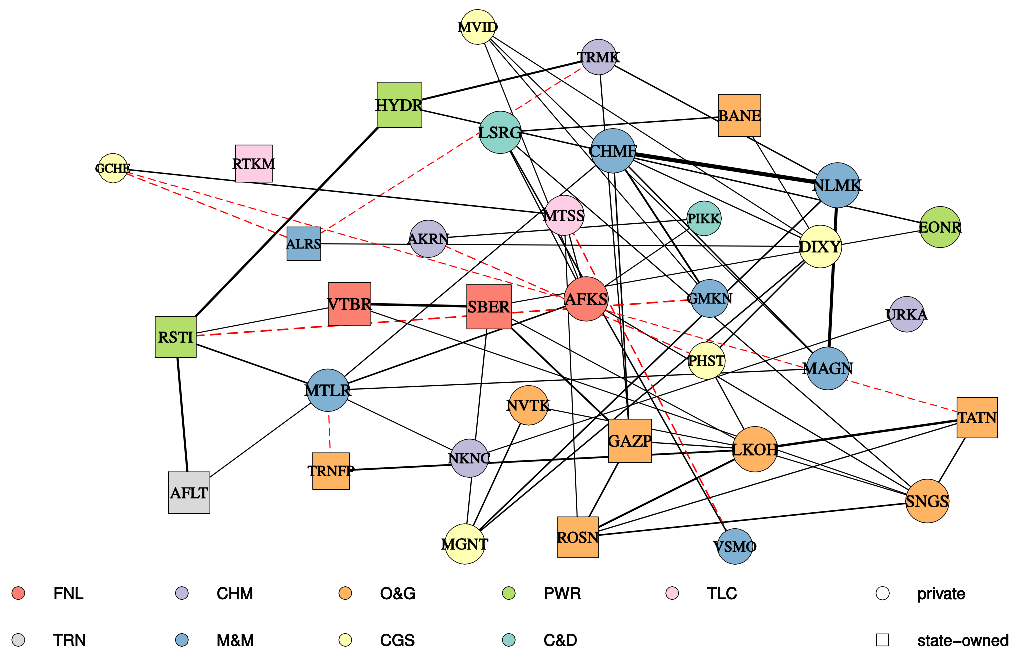

Figure 10: Dynamic correlation network, 30.12.2014

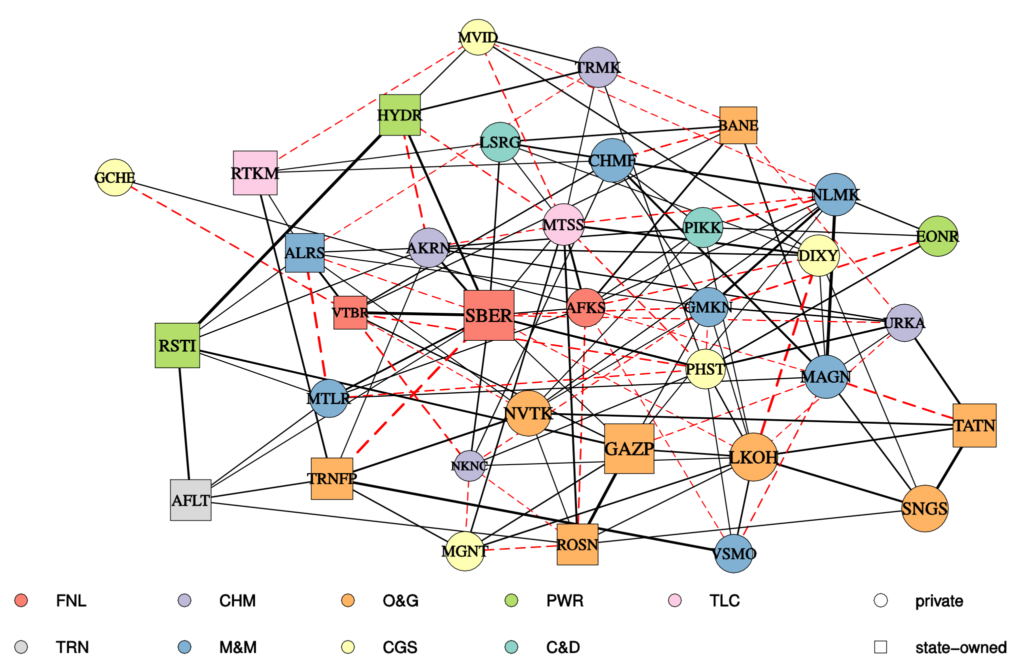

Figure 11: Dynamic correlation network, 30.12.2015

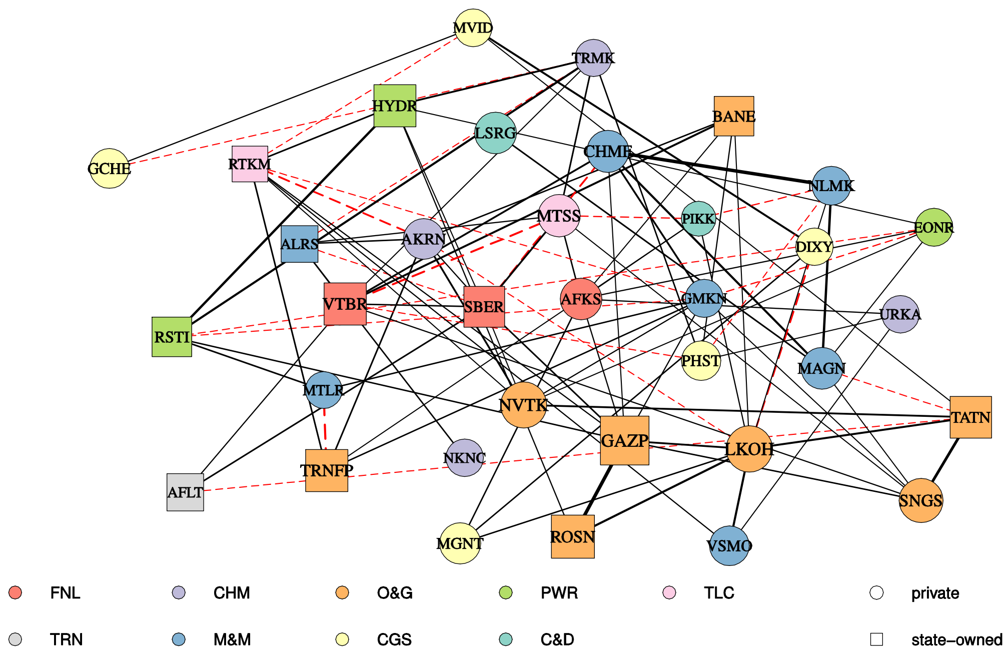

Figure 12: Vulnerability index

Figure 13: Rating scales with outlook (based on the credit ratings of major agencies on Russian economy) vs. the vulnerability indices (calculated based on principal components anaylsis of network measures). Correlation of rating scale with vulnerability index is -0.695 and with weighted vulnerability index is -0.703, both correlations significant at 1%.

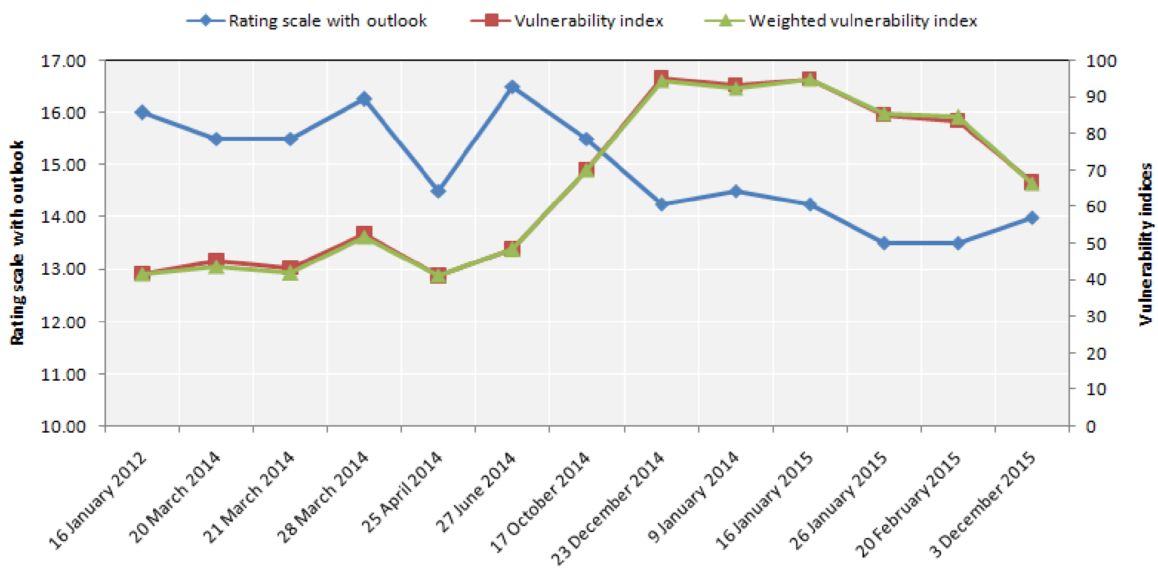

Figure 14: Weighted vulnerability, ACRA FSI and RTSVX indices

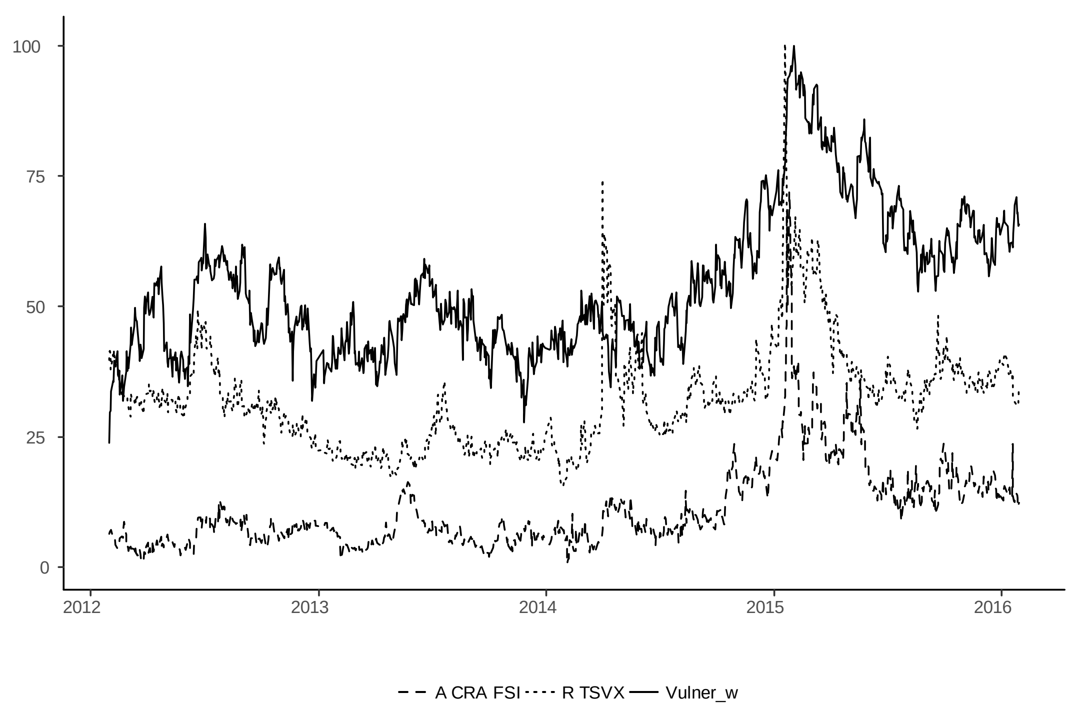

Table 1: Example

Node	k	DC	DC^{tune}
1	1	7	2.65
2	2	8	4
3	5	5	5

DC_i^{tune} with $\alpha =$ 0.5

Table 2: Stocks listed in MICEX with corresponding sector information

Ticker	Name	Ticker	Name
	Chemicals sector (CHM)		Metal and mining sector (M&M)
AKRN	Acron	ALRS	AC "Alrosa"
NKNC	PJSC "Nizhnekamskneftekhim"	CHMF	Severstal
TRMK	TMK	GMKN	OJSC MMC "Norilsk Nickel"
URKA	Uralkali	MAGN	OJSC "MMK"
	Construction and development sector (C&D)	MTLR	Mechel OAO
LSRG	OJSC LSR Group	NLMK	NLMK Group
PIKK	PIK Group	VSMO	VSMPO-AVISMA Corporation
	Consumer goods and services sector (CGS)		Oil and gas sector (O&G)
DIXY	DIXY Group	BANE	OAO ANK "Bashneft"
GCHE	PJSC "Cherkizovo Group"	GAZP	Gazprom
MGNT	OJSC "Magnit"	LKOH	OAO "Lukoil"
MVID	OJSC "M.video"	NVTK	JSC "Novatek"
PHST	JSC "Pharmstandard"	ROSN	Rosneft
	Electricity and utilities sector (PWR)	SNGS	Surgutneftegas
EONR	OAO "E.ON Rossiya"	TATN	Tatneft
HYDR	JSC "RusHydro"	TRNFP	Transneft Pref.
RSTI	PJSC "Rosseti"		Telecommunications sector (TLC)
	Financial sector (FNL)	MTSS	MTS OJSC
AFKS	AFK Sistema	RTKM	Rostelecom
SBER	Sberbank		Transport sector (TRN)
VTBR	JSC "VTB Bank"	AFLT	JSC "Aeroflot"

Table 3: Within sector calculation

Sector	firms	state firms	cap	edges	weights	neg.edges	edges*	weights*
O&G	8	5	0.567	15	1.798	0	0.536	0.064
M&M	7	1	0.126	8	1.050	1	0.381	0.050
CGS	5	0	0.047	3	0.290	0	0.300	0.029
CHM	4	0	0.039	1	0.073	0	0.167	0.012
PWR	3	2	0.025	2	0.337	0	0.667	0.112
FNL	3	2	0.145	2	0.274	0	0.667	0.091
C&D	2	0	0.007	1	0.087	0	1.000	0.087
TLC	2	1	0.042	0	0.000	0	0.000	0.000
TRN	1	1	0.003	0	0.000	0	-	-

Columns indicate from left to right for each sector: tickers, number of firms, number of state-owned or regulated firms, percentage of capitalization among considered firms, number of edges, net sum of weights, number of negative edges, normalized number of edges, and normalized sum of weights within each sector.

Table 4: Centrality measures for constant correlation model

name	sector	SCI	Cap	k	DC	DC^{abs}	DC^{+}	DC^{tune}	EC	EC^{abs}	C^{B}
GAZP	O&G	1	0.18 (1)	10	1.10 (1)	1.10 (3)	1.10 (2)	3.31 (3)	1.00 (1)	0.99 (2)	2.91 (1)
LKOH	O&G	0	0.09 (4)	11	0.99 (4)	1.19 (1)	1.09 (3)	3.61 (2)	0.97 (2)	0.98 (4)	2.59 (2)
NLMK	M&M	0	0.02 (14)	8	1.00 (3)	1.00 (5)	1.00 (4)	2.83 (5)	0.58 (7)	0.88 (6)	2.48 (3)
CHMF	M&M	0	0.02 (13)	7	0.81 (6)	0.99 (6)	0.90 (5)	2.64 (8)	0.61 (6)	1.00 (1)	2.28 (4)
SBER	FNL	1	0.10 (3)	12	1.04 (2)	1.18 (2)	1.11 (1)	3.76 (1)	0.50 (9)	0.62 (9)	2.21 (5)
SNGS	O&G	0	0.05 (7)	9	0.84 (5)	0.84 (8)	0.84 (7)	2.75 (7)	0.77 (5)	0.78 (8)	2.13 (6)
TATN	O&G	1	0.03 (12)	9	0.65 (8)	1.01 (4)	0.83 (8)	3.02 (4)	0.84 (3)	0.98 (3)	2.00 (7)
ROSN	O&G	1	0.13 (2)	6	0.61 (9)	0.79 (9)	0.70 (9)	2.18 (10)	0.79 (4)	0.90 (5)	1.90 (8)
MAGN	M&M	0	0.01 (22)	8	0.76 (7)	0.95 (7)	0.85 (6)	2.76 (6)	0.38 (11)	0.85 (7)	1.85 (9)
NVTK	O&G	0	0.07 (5)	7	0.58 (10)	0.58 (11)	0.58 (11)	2.02 (11)	0.51 (8)	0.48 (11)	1.51 (10)
VTBR	FNL	1	0.03 (9)	7	0.53 (12)	0.68 (10)	0.61 (10)	2.19 (9)	0.41 (10)	0.53 (10)	1.47 (11)
MGNT	CGS	0	0.04 (8)	7	0.56 (11)	0.56 (12)	0.56 (12)	1.97 (12)	0.36 (12)	0.41 (12)	1.36 (12)

This table shows different centrality measures for the top twelve companies according to Bonacich centrality in the case of the constant correlation model. Columns indicate from left to right for each firm: ticker, sector, indicator of state-owned or regulated firm (SCI), percentage of capitalization among considered firms (Cap), number of edges (k), net degree centrality (DC), degree centrality of adjacency matrix with absolute values (DC^{abs}), positive degree centrality (DC^{+}), tuned degree centrality with $\alpha = 0.5$ (DC^{tune}), eigenvector centrality for adjacency matrix (EC) and adjacency matrix with absolute values (EC^{abs}) and Bonacich centrality with $\beta = 0.9$ (C^{B}).

Table 5: Centrality measures for dynamic correlation model.
Pre-crisis period, 30.12.2013

name	sector	SCI	Cap	k	DC	DC^{abs}	DC^{+}	DC^{tune}	EC	EC^{abs}	C^{B}
NLMK	M&M	0	0.02 (15)	7	1.02 (2)	1.19 (7)	1.10 (5)	2.88 (12)	1.00 (1)	0.89 (2)	3.61 (1)
CHMF	M&M	0	0.01 (16)	11	0.98 (3)	1.45 (1)	1.22 (1)	3.99 (1)	0.97 (2)	1.00 (1)	3.58 (2)
SBER	FNL	1	0.11 (3)	11	0.95 (6)	1.28 (3)	1.11 (4)	3.75 (4)	0.89 (3)	0.74 (5)	3.51 (3)
GAZP	O&G	1	0.17 (1)	11	0.86 (8)	1.20 (6)	1.03 (7)	3.63 (5)	0.85 (4)	0.77 (4)	3.23 (4)
LKOH	O&G	0	0.09 (4)	9	1.05 (1)	1.21 (5)	1.13 (2)	3.31 (9)	0.71 (7)	0.70 (9)	3.19 (5)
VTBR	FNL	1	0.03 (10)	11	0.82 (10)	1.13 (11)	0.97 (10)	3.52 (7)	0.73 (6)	0.71 (7)	2.96 (6)
MAGN	M&M	0	0.00 (26)	10	0.83 (9)	1.17 (9)	1.00 (8)	3.42 (8)	0.79 (5)	0.84 (3)	2.95 (7)
SNGS	O&G	0	0.05 (6)	12	0.91 (7)	1.25 (4)	1.08 (6)	3.88 (3)	0.63 (9)	0.71 (8)	2.94 (8)
HYDR	PWR	1	0.01 (18)	12	0.97 (4)	1.28 (2)	1.13 (3)	3.92 (2)	0.62 (10)	0.73 (6)	2.77 (9)
MTLR	M&M	0	0.00 (34)	11	0.80 (11)	1.18 (8)	0.99 (9)	3.61 (6)	0.64 (8)	0.69 (10)	2.71 (10)
AFKS	FNL	0	0.02 (13)	9	0.96 (5)	0.96 (12)	0.96 (11)	2.95 (11)	0.44 (12)	0.43 (12)	2.54 (11)
RSTI	PWR	1	0.01 (22)	9	0.68 (12)	1.14 (10)	0.91 (12)	3.20 (10)	0.58 (11)	0.65 (11)	2.46 (12)

Table 6: Centrality measures for dynamic correlation model.
Crisis period, 30.12.2014

name	sector	SCI	Cap	k	DC	DC^{abs}	DC^{+}	DC^{tune}	EC	EC^{abs}	C^{B}
GAZP	O&G	1	0.17 (1)	15	1.47 (2)	1.83 (5)	1.65 (3)	5.24 (4)	0.97 (2)	0.64 (5)	6.87 (1)
LKOH	O&G	0	0.11 (3)	20	1.33 (3)	2.38 (2)	1.86 (2)	6.90 (2)	1.00 (1)	0.79 (3)	6.55 (2)
SNGS	O&G	0	0.05 (9)	9	1.20 (4)	1.20 (11)	1.20 (10)	3.28 (12)	0.78 (5)	0.43 (10)	5.64 (3)
TATN	O&G	1	0.03 (10)	15	0.87 (9)	1.80 (7)	1.34 (6)	5.19 (6)	0.80 (3)	0.64 (4)	5.23 (4)
SBER	FNL	1	0.07 (6)	21	1.51 (1)	2.94 (1)	2.23 (1)	7.86 (1)	0.40 (12)	1.00 (1)	5.06 (5)
ROSN	O&G	1	0.12 (2)	15	0.68 (12)	1.83 (6)	1.26 (9)	5.24 (5)	0.80 (4)	0.63 (6)	4.94 (6)
NVTK	O&G	0	0.07 (4)	15	1.09 (5)	1.63 (9)	1.36 (5)	4.94 (8)	0.67 (6)	0.51 (9)	4.66 (7)
RTKM	TLC	1	0.01 (16)	12	0.93 (7)	1.16 (12)	1.04 (12)	3.73 (10)	0.59 (7)	0.38 (12)	4.18 (8)
RSTI	PWR	1	0.00 (26)	10	0.99 (6)	1.34 (10)	1.16 (11)	3.65 (11)	0.47 (9)	0.39 (11)	4.15 (9)
CHMF	M&M	0	0.02 (12)	14	0.92 (8)	1.75 (8)	1.33 (8)	4.94 (7)	0.51 (8)	0.56 (8)	3.87 (10)
NLMK	M&M	0	0.02 (13)	13	0.83 (10)	1.84 (4)	1.33 (7)	4.89 (9)	0.47 (10)	0.61 (7)	3.75 (11)
MTSS	TLC	0	0.02 (15)	20	0.74 (11)	2.37 (3)	1.56 (4)	6.89 (3)	0.45 (11)	0.82 (2)	3.43 (12)

Table 7: Centrality measures for dynamic correlation model.
Post-crisis period, 30.12.2015

name	sector	SCI	Cap	k	DC	DC^{abs}	DC^{+}	DC^{tune}	EC	EC^{abs}	C^{B}
GAZP	O&G	1	0.14 (1)	11	1.36 (1)	1.51 (5)	1.44 (1)	4.08 (5)	1.00 (1)	0.90 (4)	4.51 (1)
LKOH	O&G	0	0.09 (4)	12	1.14 (2)	1.69 (2)	1.41 (2)	4.50 (3)	0.90 (2)	0.86 (5)	3.93 (2)
ROSN	O&G	1	0.12 (2)	8	0.85 (5)	1.04 (12)	0.94 (9)	2.89 (12)	0.78 (3)	0.69 (7)	3.31 (3)
SNGS	O&G	0	0.05 (7)	11	0.95 (4)	1.24 (8)	1.10 (7)	3.70 (8)	0.61 (4)	0.74 (6)	3.08 (4)
NVTK	O&G	0	0.08 (5)	12	1.13 (3)	1.28 (6)	1.20 (3)	3.91 (6)	0.51 (6)	0.66 (10)	3.06 (5)
TATN	O&G	1	0.03 (10)	9	0.72 (10)	1.15 (9)	0.94 (10)	3.22 (11)	0.57 (5)	0.67 (8)	2.69 (6)
VTBR	FNL	1	0.05 (9)	13	0.79 (6)	1.57 (4)	1.18 (6)	4.52 (2)	0.43 (9)	0.93 (3)	2.27 (7)
AFKS	FNL	0	0.01 (22)	10	0.73 (9)	1.09 (10)	0.91 (11)	3.30 (9)	0.42 (10)	0.57 (11)	2.21 (8)
SBER	FNL	1	0.10 (3)	15	0.66 (12)	1.69 (1)	1.18 (5)	5.04 (1)	0.43 (8)	0.99 (2)	2.21 (9)
HYDR	PWR	1	0.01 (18)	11	0.77 (8)	1.27 (7)	1.02 (8)	3.74 (7)	0.44 (7)	0.66 (9)	2.18 (10)
CHMF	M&M	0	0.02 (12)	12	0.78 (7)	1.62 (3)	1.20 (4)	4.41 (4)	0.32 (12)	1.00 (1)	2.18 (11)
MGNT	CGS	0	0.05 (8)	10	0.70 (11)	1.05 (11)	0.87 (12)	3.24 (10)	0.38 (11)	0.54 (12)	2.12 (12)

Table 8: Coefficients obtained from principal components analysis using network measures

Coefficients of PCA	Non-weighted	Weighted
Average of Bonacich centralities	0.2530	–
Weighted average of Bonacich centralities	–	0.2817
Number of edges	0.3939	0.3911
Number of negative edges	0.3699	0.3681
Sum of positive weights	0.3966	0.3930
Sum of absolute values of weights	0.3917	0.3889
Absolute values of eigenvalues	0.3383	0.3359
Average path length	−0.3847	−0.3803
Diameter	−0.2662	−0.2629
Explained variance by the first component	78%	79%

The table shows the coefficients for the first component obtained from the principal components analysis using the network measures. The only eigenvalue that was greater than 1 was that of the first component. Under the assumption of multivariate normality, all coefficients in the table are significant at 1%. However, we note that the null hypothesis that the network measures follow a multivariate normal distribution is rejected at 1%. The first principal components, which yield 78% and 79% explained sample variance respectively, are used to create the vulnerability and weighted vulnerability indices.

Table 9: Credit ratings history and vulnerability and weighted vulnerability indices

Agencies	Credit rating	Outlook	Dates	R.S.	R.S., out	Vulnerability index	Weighted Vuln. Index
Fitch	BBB	stable	16.01.2012	16.00	16.00	41.6864	41.4458
S&P	BBB	negative	20.03.2014	16.00	15.50	44.9985	43.7273
Fitch	BBB	negative	21.03.2014	16.00	15.50	43.2866	41.8201
Moody's	Baa1	neg. watch	28.03.2014	17.00	16.25	52.3645	51.6415
S&P	BBB-	negative	25.04.2014	15.00	14.50	40.9283	41.1452
Moody's	Baa1	negative	27.06.2014	17.00	16.50	48.4352	48.2168
Moody's	Baa2	negative	17.10.2014	16.00	15.50	70.0115	70.1437
S&P	BBB-	neg. watch	23.12.2014	15.00	14.25	95.0310	94.3106
Fitch	BBB-	negative	09.01.2015	15.00	14.50	93.0601	92.2926
Moody's	Baa3	neg. watch	16.01.2015	15.00	14.25	94.7709	94.8840
S&P	BB+	negative	26.01.2015	14.00	13.50	85.1122	85.3533
Moody's	Ba1	negative	20.02.2015	14.00	13.50	83.3296	84.4610
Moody's	Ba1	stable	03.12.2015	14.00	14.00	66.5019	66.2527

The table shows the credit ratings history for the Russian economy issued on various dates by Fitch, Standard and Poor's and Moody's credit ratings institutions. All possible ratings are put to a numbered scale from 0 to 24 to create the R.S: rating scale variable. For a "negative" outlook a 0.5 point is taken away from the rating scale. For a "watch" a 0.25 point is taken away from the rating scale. Hence a "negative watch" implies a 0.75-point reduction. This way we created the R.S. out variable. Vulnerability and weighted vulnerability indices are calculated from a principal components analysis of the network measures, see Table 9. Correlation between R.S. out and the vulnerability index is -0.695 and with the weighted vulnerability index is -0.703, both statistically significant at 1%.

Table 10: Correlations between ACRA Financial Stress Index and Russian Volatility Index RTSVX using different measures of network connectedness

Correlations of . with .	ACRA FSI	RTSVX
Average of Bonacich centralities	0.3369	0.2726
Weighted average of Bonacich centralities	0.4507	0.3820
Number of edges	0.7802	0.5145
Number of negative edges	0.7844	0.5036
Sum of positive weights	0.7951	0.5552
Sum of absolute values of weights	0.8225	0.5684
Absolute values of eigenvalues	0.6764	0.5060
Average path length	−0.6570	−0.3907
Diameter	−0.3868	−0.2093
Vulnerability index	0.7639	0.5125
Weighted vulnerability index	0.7685	0.5199

The table shows correlations between the ACRA and RTSV indices and the network measures as well as the vulnerability indices. A vulnerability index is calculated as the first principal component of all the network variables listed in this table. Afterwards this principal component is rescaled to [0,100]. Weights are the market capitalizations of the stocks. Missing values for the Russian Volatility Index RTSVX are linearly interpolated. All correlations in this table are significant at 1%.

Table 11: Canonical correlation analysis

Variable list	Lag 0 Coefficients	Lag 0 St. coefficients	Lag 0 Corr(factor,.)	Lag 1 Coefficients	Lag 1 St. coefficients	Lag 1 Corr(factor,.)	Lag 2 Coefficients	Lag 2 St. coefficients	Lag 2 Corr(factor,.)
smoothed factor estimate	1.9558*** (0.0000)	1.0000	.						
SP500 returns (in rub)	−0.4505 (0.3080)	−0.5791	0.0234 (0.4503)	−0.1446 (0.7590)	−0.1859	0.0446 (0.1501)	0.1901 (0.6240)	0.2443	−0.0460 (0.1382)
Brent oil returns (in rub)	−0.0303 (0.6510)	−0.0581	0.0168 (0.5874)	−0.0994 (0.1390)	-0.1907	−0.0581* (0.0606)	0.0120 (0.8560)	0.0230	−0.0249 (0.4231)
USD/RUB returns	0.3693 (0.2320)	0.4840	0.0393 (0.2048)	1.2678*** (0.0000)	1.6611	0.0736** (0.0175)	−0.4044* (0.0660)	−0.5294	−0.0436 (0.1602)
MICEX returns	0.0005 (0.9960)	0.0007	0.0018 (0.9541)	0.2507** (0.0340)	0.3154	0.0151 (0.6256)	−0.1756 (0.1250)	−0.2208	−0.0638** (0.0395)
HSI returns (in rub)	−0.0770 (0.6720)	−0.1173	0.0425 (0.1704)	0.0198 (0.9140)	0.0302	0.0368 (0.2358)	0.1516 (0.4050)	0.2308	−0.0371 (0.2317)
MSCIEM returns (in rub)	0.6226** (0.0450)	0.7948	0.0648** (0.0402)	−0.1575 (0.6150)	−0.2009	0.0387 (0.2213)	−0.1163 (0.7070)	−0.1483	−0.0636** (0.0442)
MSCIW returns (in rub)	−0.4688 (0.4200)	−0.5705	0.0448 (0.1817)	−0.7444 (0.2080)	−0.9058	0.0450 (0.1802)	−0.0494 (0.9290)	−0.0601	−0.0619* (0.0651)
VIX	−0.3417** (0.0290)	−1.1595	−0.0165 (0.5946)	−0.0944 (0.6450)	−0.3202	−0.0051 (0.8683)	0.3825** (0.0150)	1.2946	−0.0068 (0.8275)
SP500 sq. returns (in rub)	0.3183*** (0.0010)	1.7833	0.0852*** (0.0059)	−0.1101 (0.2660)	−0.6170	−0.0379 (0.2212)	−0.1960* (0.0670)	−1.0984	−0.0620** (0.0454)
Brent oil sq. returns (in rub)	0.0031 (0.8360)	0.0289	0.0043 (0.8884)	−0.0051 (0.7380)	−0.0469	−0.0214 (0.4909)	−0.0090 (0.5500)	−0.0835	−0.0294 (0.3441)
USD/RUB sq. returns	0.1121* (0.0810)	0.7774	0.0625** (0.0435)	0.0489 (0.4570)	0.3390	−0.0247 (0.4256)	−0.0826 (0.2130)	−0.5724	−0.0604* (0.0513)
MICEX sq. returns	−0.0087 (0.7310)	−0.0436	−0.0061 (0.8453)	−0.0024 (0.9260)	−0.0121	−0.0240 (0.4385)	0.0033 (0.8940)	0.0167	0.0279 (0.3690)
HSI sq. returns (in rub)	0.0811 (0.1800)	0.5663	0.0507 (0.1016)	0.0896 (0.1200)	0.6254	−0.0124 (0.6898)	0.0390 (0.4960)	0.2720	−0.0490 (0.1142)
MSCIEM sq. returns (in rub)	−0.0525 (0.6560)	−0.3062	0.0512 (0.1052)	−0.2133* (0.0660)	−1.2441	−0.0294 (0.3528)	−0.1322 (0.2530)	−0.7714	−0.0607* (0.0550)
MSCIW sq. returns (in rub)	−0.3976** (0.0190)	−2.3147	0.0659** (0.0493)	0.1451 (0.4060)	0.8450	−0.0318 (0.3433)	0.3053* (0.0920)	1.7772	−0.0619* (0.0650)
Canonical correlation	Wilk's lambda	Pillai's trace	Lawley-Hotelling	Roy's largest root					
0.2883	0.9169 (0.0033)	0.0831 (0.0033)	0.0906 (0.0033)	0.0906 (0.0033)					

Note: This table shows the canonical correlation analysis results between the smoothed factor estimate (first set of variables) and external variables with their lags (second set of variables). The columns show the raw coefficients and corresponding p-values, the standardized coefficients and Pearson correlations between the factor estimate and external variables and corresponding p-values. Significance levels: * 10%, ** 5%, *** 1%.

KOKKUVÕTE

Aktsiate kaardistamine MICEX'il: kes on Moskva aktsiaturu keskmes?

Käesolevas uurimuses teeme kindlaks enim omavahel seotud firmad Venemaa aktsiate turul perioodil 01.12.2011 kuni 29.01.2016 kasutades nii staatilisi kui dünaamilisi mudeleid. Esmalt toetume VAR mudelile ning Kalmani filtrile, et elimineerida mittevaadeldav ühine faktor. Seejärel arvutame osakorrelatsioonid tingimuslikest korrelatsioonihinnangutest, mis on omakorda leitud Bollerslevi (1990) konstantse tingimusliku korrelatsiooni GARCH mudelist (cCC-GARCH) ning Aielli (2008) mõjusa dünaamilise tingimusliku korrelatsiooni GARCH mudelist (cDCC-GARCH). Arvestades, et leitud osakorrelatsioone kasutame hiljem Gaussi graafilises mudelis (GGM), on cCC-GARCH mudeli abil võimalik hinnata, kuidas on ettevõtted omavahel seotud vaatlusaluse perioodi jooksul, ning cDCC-GARCH aitab leida ühendusi mingil konkreetsel ajahetkel. Töös analüüsime ka mõningate võrgustikuteooria põhinäitajate (servade arv graafikul, nende kaalude summa ning keskmine marsruudipikkus) dünaamikat. Lisaks arvutame süsteemi haavatavuse kahte liiki indeksid läbi peakomponentide analüüsi, mis kaasab võrgustikku iseloomustavad põhinäitajad. Üks neist kasutab Bonacich´i tsentraalsuste keskmist ning teine Bonacich´i tsentraalsuste kaalutud keskmist. Kaaludena võtame aluseks igapäevase turukapitalisatsiooninäitaja. Saadud indeksite suurusjärk annab mõõte kogu majanduse üldisele süsteemsele riskile, kuna see näitab, kui tundlik on süsteem üldistele negatiivsetele šokkidele. Selleks, et luua seoste võrgustikku, kasutame Gaussi graafilist mudelit. Nimetatud meetod võimaldab hõlmata lineaarset kahesuunalist sõltuvust kahe muutuja vahel, mida mõõdab osakorrelatsioon süsteemis. Kahe firma vaheline lineaarne sõltuvus näitab, kuivõrd need firmad lliguvad samas suunas turutingimuste ning välitegurite muutudes.

Analüüsi tulemused näitavad, et enim seotud ettevõtted on eranaftafirma Lukoil ning suurimad riigiettevõtted Gazprom ja Sberbank. Need firmad on ka turul suurimad süsteemse riski panustajad, erandina Sberbank, kelle asemel on NLMK Grupp. Kõik vaatluse all olevad võrgustiku põhinäitajad peegeldavad edukalt 2014-2015.a aset leidnud majandussurutist ning ebastabiilsust Venemaa majanduses. Ilmneb, et artiklis vaatluse all olevad haavatavuse indeksid peegeldavad samasuunalisi liikumisi ning on tugevalt korreleerunud valitsuse võla krediidireitinguga, mis on noteeritud Standard&Poor´s, Moody ja Fitch poolt, ning ka Venemaa volatiilsusindeksiga RTSVX ja finantsstressiindeksiga ACRA FSI.