Mapping the Stocks in MICEX: Who Is Central in Moscow Stock Exchange?

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

JEL classification: C01, C13, C32, C52

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Preliminary version

Abstract

In this article we use partial correlations to derive bidirectional connections between major firms listed in MICEX. We obtain coefficients of partial correlation from the correlation estimates of constant conditional correlation GARCH (CCC-GARCH) and 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 shock propagation and in terms of connectedness with others. Moreover, we analyze some macro characteristics of the network over time and measure the system vulnerability to external shocks. Our findings suggest that during the crisis interconnectedness between firms strengthens and the system becomes more vulnerable to systemic shocks. In addition, we found that the most connected firms are Sberbank and Lukoil, while most central in terms of systemic risk are Gazprom and FGC UES.

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1 Introduction

The financial crisis of 2008 exposed the needs for better understanding of risks in financial market and in economy in general. Specifically, systemic risk became one of the most important issues and encouraged a lot of literature in finance mainly after the crisis of 2008.

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There are several approaches to measure systemic risk such as SRISK measure proposed by Brownless and Engle (2016) or CoVaR method by Adrian and Brunnermeier (2016) among many others.

Linkages between firms is one of the key channels of how systemic risk spreads throughout the system. Once a firm experiences a negative extrenalities it becomes dangerous not only for the firm and its bondolders, as the capitalizations of the firm fall, but also might negatively affect the whole economy through the trading or loan channels. Hence, estimation of these connections play a central role in understanding behaviour of such systemic risk. A widely used approach to describe the connectedness among the number of companies is the usage of graphs as a network theory application. There is a number of papers, which describe financial and economic data from the network theory perspective. For example, interbank connections in the paper of Brownless, Hans, Nualart (2014), interconnectedness among financial institutions (Diebold, Yilmaz (2014)) and among the major corporation in U.S.(Bariggozi, Brownless (2016)) and Australia (Anufriev and Panchenko (2015)).

Moreover, network theory helps us not only to visualize graph of connectedness but also to make some conclusions based on appropriate measures of network theory. In our paper we identify top connected firms and top systemic contributors in static model and over time in Russian Stock Market. In addition, we calculate vulnerability of the system as an average of the quantitative measures of the possible fall of the system caused by a negative shock to each firm. This magnitude can be used as a measure of overall systemic risk in the entire economy, as it shows sensitivity of the system to negative externalities in general.

In order to construct a network of connectedness we use the Gaussian Graphical Model (GGM) approach, which is quite new for finance, while it is widely used in biometrics (see for example Krumsiek et al. (2011), Rice et al. (2005)). The idea of GGM is to capture linear bidirectional dependence between two variables measured with partial correlation conditional on other elements in the system. Separated linear dependence between a pair of firms showing partial correlation can be used as a channel through which a shock can be transmitted from one firm to another. GGM allows reconstructing graphs of interconnectedness between components of multivariate random variable, where nodes of the graph represent elements of this multivariate vector and edges show their conditional dependence. This type of network of partial correlations between firms shows not only how well or not the whole economy is connected, but also how the shocks propagate therein, if some company suffers from negative exogenous effects.

Firms can be connected in different ways. For example, they can be connected directly via trading relationships. However, to study interconnectedness in financial market we need more frequent data, than, for instance, companies' balance sheets. One of the convenient ways to identify connectedness between firms is to consider co-movements of their stock returns (see Diebold, 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 to the true unobservable connections between firms. Moreover, such frequent data allows us to calculate daily measure of systemic risk, which is a considerable advantage for policymakers.

General approach for financial data is to take into account volatility connectedness (see Diebold, Yilmaz (2014)). Volatility often represents fear of investors, hence volatility connectedness is a kind of fear connectedness between investors. For example, in situations of uncertainty, such as financial crises, investors fear more and volatility increases. In a situation where two firms are connected, increasing volatility in one firm's stock returns will lead to volatility rise of the second one, that is why we should capture volatility connectedness between two firms.

In this paper, we bring together the ideas from the papers by Anufriev and Panchenko (2015), 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 the returns, if not filtered out, will lead to spuriously high correlations and a fully connected network. Moreover, we compute partial correlations from the conditional correlation estimates obtained from the Constant Conditional Correlation GARCH model of Bollerslev (1990) and consistent Dynamic Conditional Correlation GARCH model of Aielli (2008). The former model gives an idea on 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 estimation. This method successfully avoids the trap of attenuation biases observed in cDCC-GARCH model.[1]

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

The paper is structured as follows. Section 2 introduces network construction based on Gaussian graphical model. Section 3 discusses the crucial measures of network analysis. In Section 4 we introduce the data we use and in the following Section 5 we discuss the

[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.

econometric models. Section 6 describes estimation procedure of the econometric models. Section 7 shows empirical application for Russian Stock Market. Finally, Section 8 details further discussion. Section 9 concludes the paper.

2 Network construction

Let's 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 $w_{i,j}$ that shows the strength of connectedness between nodes i and j.

To construct a network we use the concept of Gaussian graphical models based on the work of Buhlmann and Van De Geer (2011), Hastie et al. (2009) and Anufriev and Panchenko (2015). A Gaussian Graphical Model (GGM) helps to construct a conditional 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 multivariate random variable $X = \{X_1, ..., X_n\}$.

According to 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, *i.e.* between components X_i and X_j of multivariate variable X, $\rho_{i,j|\cdot}$, 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 high connection between two variables generated by dependence of these both variables on a third one, the partial correlation measure their connection eliminating the influence of the third variable from both of them. Thus, two nodes are connected $(i, j) \in E$, if and only if they are not conditionally independent, i.e. $\rho_{i,j|\cdot} \neq 0$. Moreover, partial correlation between any pairs of nodes is used in GGM as a weight of an edge in the graph corresponding to that pair, i.e. $w_{i,j} = \rho_{i,j|\cdot}$ is the weight of the edge between nodes i and j.

Before considering how partial correlation can be obtained, let us recall that coefficient of correlation between components X_i and X_j, $r_{i,j}$, is the coefficient of covariance between them divided by standard deviation of each component, i.e.

$$r_{i,j} = \frac{\sigma_{i,j}}{\sigma_i \sigma_j}, \tag{1}$$

where $\sigma_{i,j}$ is the covariance between X_i and X_j, and $\sigma_i = \sqrt{\sigma_{i,i}}$ is the standard deviation of variable X_i. In other words, correlation between any two components can be expressed from the covariance matrix $\Omega = Cov(X)$. If we denote correlation matrix of multivariate random variable X as R with $r_{i,j}$ as the ij-th element of this matrix, then we can rewrite the equation (1) in the matrix form as follows:

$$R = D_{\Omega}^{-1/2} \Omega D_{\Omega}^{-1/2}. \tag{2}$$

Here $D_{\Omega} = diag\{\sigma_1^2, ..., \sigma_n^2\}$ is a diagonal matrix composed of the diagonal elements of the covariance matrix Ω.

While ordinary correlation relates to the covariance matrix Ω, the inverse of non-singular covariance matrix $K = \Omega^{-1}$, also called concentration matrix, contains information of partial correlation. Well-known result (see again Buhlmann and Van De Geer (2011), Hastie et al. (2009)) is that partial correlation can be derived as

$$\rho_{i,j|\cdot} = -\frac{k_{i,j}}{\sqrt{k_{i,i}k_{j,j}}} \tag{3}$$

where $k_{i,j}$ is the ij-th element of the matrix $K = \Omega^{-1}$. As can be noticed, the equations of correlation and partial correlation are similar. Indeed, if we suppose in the equation (3) $k_{i,j} = \sigma_{i,j}$, i.e. it is the ij-th element of covariance matrix Ω, then partial correlation equals to ordinary correlation except the sign. The matrix of partial correlations can be expressed similarly as follows:

$$P = -D_K^{-1/2} K D_K^{-1/2}. \tag{4}$$

It can be shown that this equation also holds with the $K = R^{-1}$. Indeed, we can get from (2) that

$$R^{-1} = D_{\Omega}^{1/2} \Omega^{-1} D_{\Omega}^{1/2}$$

It is easy to see here that diagonal elements of the matrix R^{-1} is $k_{i,i}\sigma_i^2$, where $k_{i,i}$ is the diagonal element of Ω^{-1}. Expressing the Ω^{-1} from the last equation and substituting it in (4) we have

$$P = -D_K^{-1/2} D_{\Omega}^{-1/2} R^{-1} D_{\Omega}^{-1/2} D_K^{-1/2}.$$

As the D_K and D_{Ω} are diagonal matrices with the elements on diagonal $k_{i,i}$ and σ_i^2 respectively, it is easy to show that their multiplication gives diagonal matrix with elements $k_{i.i}\sigma_i^2$. Thus, the following equation holds $D_{\Omega^{-1}} D_{\Omega} = D_{R^{-1}}$. It means that the matrix of partial correlation is related to the matrix of ordinary correlation in the following way

$$P = -D_{R^{-1}}^{-1/2} R^{-1} D_{R^{-1}}^{-1/2}. \tag{5}$$

That is, (4) holds both for the $K = \Omega^{-1}$ and $K = R^{-1}$.

The other common way to represent a graph is adjacency matrix (see Jackson (2008)). Adjacency matrix A is a matrix of size $n \times n$ with a non-zero ij-th element if the nodes i and j are connected and with the zeros otherwise. For an undirected weighted graph the adjacency matrix is symmetric with entries given by weights of the appropriate nodes. In the case of GGM the adjacency matrix contains coefficient of partial correlation $\rho_{i,j|.}$ as the ij-th element for $i \neq j$ and zeros on the diagonal. Notice that diagonal elements of matrix of partial correlations are minus units given that equation (3) holds. That is, in the matrix form we have:

$$A = I + P = I - D_K^{-1/2} K D_K^{-1/2} \tag{6}$$

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

Finally it is important to note the sign of the entries of adjacency matrix constructed on the base of partial correlation. In network theory weights of edges are usually assumed to be positive. However, as value of partial correlation spans between -1 and 1, some entries of adjacency matrix A can be negative as well as positive, therefore we cannot simply assume that weights of network are positive in the case of GGM. There is literature in social network analysis, where negative values of edges are used (see for example J. Kunegis et al. (2009)). Negative connections there correspond to the relationship between foes, while positive values correspond to the relationship between friends, and an individual can have both friends and foes. In finance such kind of relations are rare although Barigozzi and Brownlees (2016) also have found negative edges in the network of U.S. Bluechips constructed with help of partial correlations and Granger causality.

As it will be shown later, in our paper we get both positive and negative connections, therefore we consider negative edges similar to relationship between foes: negative value of partial correlation between two firms means that the rise of one company can encourage (or can be encouraged by) the fall of dependent firms and vice versa. 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 network of interconnectedness in general and the features of each node in the network. Macro characteristics include measures such as diameter, average path length, number of edges etc. (for more details see Jackson (2008)). Micro characteristics can help us find the nodes that play an important role in the system.

One of the most substantial characteristics of node in a network is *centrality*. It can be interpreted at least in two ways for financial market. Firstly, used in social science mostly, it shows the importance of a node in terms of connection with other nodes (see, for example, Jackson (2008)). The second way is that centrality represents importance of a node in terms of systemic risk (e.g. Acemoglu et al. (2015)). For example, a negative shock of a more central node results in larger fall of the system in general rather than a negative shock of a less central agent. Mainly, nodes found in terms of these two interpretations coincide, that is the most connected agents are systemically important. However, if network has both positive and negative edges, which might be the case for networks based on partial correlations, it 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, in case of unweighted network, is calculated simply as a number of its adjacencies[2]. Commonly used method for calculating degree centrality for weighted graph is to sum weights for each nodes (see Newman (2004)). However, in case of a network with positive and negative ties, if we want to differentiate the meaning of centrality, it is helpful to distinguish degree centrality as follows:

$$\begin{aligned} DC_i^{net} &= \sum_{j=1}^{n} a_{i,j}, \qquad DC^{net} = A \cdot 1, \\ DC_i^{abs} &= \sum_{j=1}^{n} \left| a_{i,j} \right|, \qquad DC^{abs} = abs(A) \cdot 1 \\ DC_i^{+} &= \sum_{j=1}^{n} \{ a_{i,j} | a_{i,j} > 0 \}. \end{aligned} \tag{7}$$

where A is the adjacency matrix of the network and $abs(A)$ is the absolute value of each element of the adjacency matrix. DC_i^{net} shows the net sum of weights of the node i. In terms of connections with other agents this measure is uninformative, because it does not distinguish, whether node i has only positive connections or its connections have different signs. For example, if a node has some positively and negatively connected neighbours, then effects transmitted from the node i will cancel each other out. It should be noted here, that negative shock transmitted through positive links has adverse consequences for one's neighbours, while the shock propagated through negative channels has favourable effect for them.

[2]In some literature, *e.g.* Jackson (2008), normalized degree centrality is used for 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.

In terms of systemic risk contribution net degree centrality represents the net immediate effect on i's neighbours, that is negative effects of the shock on i's neighbours minus a positive one. DC_i^{abs} takes into account the absolute values of strengths of relations, therefore, it is valid to measure connectedness with its adjacent nodes without separating them as positive and negative relations. Absolute degree centrality gives total effect on neighbours in case of shock transmission. In other words, it shows total impact of a node on the adjacent ones. To measure only positive connections, we use DC_i^+, which allows to capture strength of positive relations and shows importance of a node in terms of consequences of a negative shock on one's neighbours .

If we want to identify the agents who are central in terms of connections with others, we can specify a measure of connectedness. The sum of the absolute weights measures total involvement into connectedness of the network but does not take into consideration the number of the edges of each node. To show this problem let's consider an example illustrated by the Figure 1. Let node 1 connect only with node 2 with the value of connectedness $w_{1,2} = 7$ and let node 3 have five neighbours and let strength of connectedness with each of them be equal to 1. The degree centrality[3] of the node 1 according to the last equation (7) exceeds the degree centrality of the node 3. It is intuitively clear that the node 3 is more central compared to the number of neighbours perspective. So it is of important to take into account both sum of weights and the number of neighbors when calculating the node centrality.

Opsahl, Agneessens, Skvoretz (2010) proposed using tuning parameter α to measure centrality which determines preference of number of edges over node's weights. Formally, they use the following measure of degree centrality:

$$DC_i^{tune} = k_i^{1-\alpha} \times DC_i^{\alpha}. \tag{8}$$

Here k_i is the number of adjacencies of the node i and DC_i is one of the introduced degree centralities above. It should be noted that the equation (8) coincides with the equations in (7) with $\alpha = 1$, and $\alpha = 0$ gives us the number of edges of node, k_i. In other words DC_i^{tune} measures degree centrality giving more value to the weights of node with α close to one and it gives more value to the number of edges with α close to zero. See Table 1 for the example comparing DC and DC^{tune}.

The other measure of centrality is *eigenvector centrality.* It characterizes centrality of a node based on the neighbors' centrality. Again, it is possible to distinguish this centrality measure in terms of connections with others and in terms of systemic risk, but before that let briefly look at the idea of eigenvector centrality in general.

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

Let C^e be the centrality vector of a given network and $C^e(i)$ is the centrality of a 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 (see Bonacich (1987), Jackson (2008)). Formally, $\lambda C^e(i) = \sum_{j=1}^{n} w_{i,j} C^e(j)$, where λ is some proportional factor. In matrix form it can be written as

$$\lambda C^e = AC^e \tag{9}$$

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

The advantage of eigenvector centrality is that it can be applied to networks with different signs of connections (Bonacich (2007)). So we can apply it for our adjacency matrix based on partial correlations. Moreover, in terms of systemic risk eigenvector centrality shows how far and, hence, how fast can a shock be propagated (Anufriev and Panchenko (2015)). In addition, for a graph with different signs of weights it is be possible to look at eigenvector centrality based on adjacency matrix of absolute values of partial correlations. This kind of centrality will give us total connections of node in terms of absolute connections of one's neighbour.

An important question for systemic risk is to find a quantitative measure of the possible fall of the system, caused by a negative shock to a certain firm. This measure can be derived with help of network theory as well. Let e be the shock experienced by some firm i. Mathematically, this shock, in terms of the whole system, can be written as a vector with non-zero i-th element and with zeros for the rest. Firstly, the shock will be transmitted to node i's neighbour as $A \cdot e$, which following Anufriev and Panchenko (2015) we call a first-order effect. Notice, that the first-order effect of the node i is exactly the net degree centrality of this node, DC_i^{net}. Next, this effect will spread from the neighbours of node i to the nodes linked by them and can be calculated as $A^2 \cdot e$. This is called a second-order effect. Following this idea we can derive k-th-order effect. The total effect on the system from the negative shock on node i will be as follows:

$$e + A \cdot e + A^2 \cdot e + A^3 \cdot e + ... = \sum_{k=0}^{\infty} A^k e = (I - A)^{-1} e \tag{10}$$

It should be noted that the last equation holds only under the assumption that all eigenvalues of adjacency matrix A are in the unit circle. If we denote $T = (I - A)^{-1}$, then $T \cdot e$ shows total effect of the shock on all the agents in the system. Summing all the elements of the vector $T \cdot e$ we can obtain the total effect on the system caused by the shock on one node.

It has been shown that Bonacich centrality with $\beta = 1$ is linked with total effect matrix T (Anufriev and Panchenko (2015)). Indeed, Bonacich centrality, also known as beta-centrality, is calculated as

$$C^B(\beta) = \sum_{k=1}^{\infty} \beta^{k-1} A^k \cdot 1 = (I - \beta A)^{-1} A \cdot 1$$

In case of $\beta = 1$ beta-centrality

$$C^B(1) = A \cdot 1 + A^2 \cdot 1 + A^3 \cdot 1 + ... = T \cdot 1 - 1 \tag{11}$$

Equation 11 shows cumulative effect from the first-order of a unit shock $e = 1$. It is easy to see that beta-centrality shows total effect of the shock minus the value of this shock. In other words, it measures the value of consequences of shocks of each node separately. It should be noted again that to apply this measure eigenvalues of the adjacency matrix ought to be inside unit circle.

It is of interest to look at macro characteristics of the network such as number of edges, diameter and average path length of the network in dynamics. The number of edges is simply the number of the connections in our network. The diameter is the largest path between any two nodes. In other words it shows maximum steps needed for the shock on one node to reach the other nodes. *The average path length* measures the average shortest path between nodes, so it shows the average number of steps of shock propagation in terms of network. All three characteristics are strongly related: the average path length is bounded above by the diameter and coincides with it in case of a fully connected network (that is when all nodes are interconnected); the more the number of the edges in the network the less average path length and diameter. In other words, the more connected a network is the more is the number of edges in it and the less are the diameter and average path length. We will look at these characteristics over time to see at which periods our network was more or less connected.

Moreover, it is of importance to define the periods when system in general was more vulnerable. In order to do so, we calculate the average of Bonacich centrality measures with $\beta = 1$ at each time. To distinguish the possibility that larger firms may cause larger falls, we also consider Bonacich centralities weighted with capitalization of assets of each firm. These measures can help to compare conditions of financial systems over the time in terms of sensitivity to negative externalities.

4 Data on the stocks in MICEX

We use daily stock returns to construct the network of market interconnection 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 calculation of the Moscow Exchange Indices such as MICEX and RTS. These indices are constituted by the 50 most liquid Russian stocks of the largest Russian issuers from the main sectors of the economy. The data was obtained from the Moscow Stock Exchange. 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 36 firms. The list of the companies with tickers and sectoral classifications is provided in Table 10.

While studying the data, we noticed that there are outliers in the stock returns. When we compared these outliers with the sectoral indices and 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 annexation of Crimea to Russian Federation and it's possible consequences.[4] The rest of the outliers in stock returns were stock specific. Therefore, using Hampel filter of Hampel *et al* (1986), we replaced the stock specific outliers with local medians.[5] 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 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 calculation may not eliminate these common factors, we may spuriously end up with a fully connected network. Therefore we need to filter out common factor from the return data before carrying out network analysis. For simplicity we assume that all stock returns might be affected by one common unobservable factor. This could be political background, index of a leading stock market, GDP etc.

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

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

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

5 Econometric Models

In our paper we use the correlations obtained from constant conditional correlations GARCH (CCC-GARCH) model of Bollerslev (1990) and consistent dynamic conditional correlations GARCH (cDCC-GARCH) model of Aielli (2008). We construct our equations as follows.

5.1 Conditional Mean

We define r_t to be a kx1 vector of return series, then the return equation is given by:

$$\begin{aligned} r_t &= \mu_1 + \mu_2 Out_t + \beta r_{t-1} + c f_t + \varepsilon_t \\ f_t &= \rho f_{t-1} + \omega_t \\ \begin{pmatrix} \varepsilon_t \\ \omega_t \end{pmatrix} &\backsim N\left(0_k, \begin{bmatrix} H_t & 0 \\ 0 & \Sigma \end{bmatrix}\right) \end{aligned} \tag{12}$$

where β is a kxk matrix, μ_1, μ_2 and c are kx1 vectors and c and ρ are scalar parameters, 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 factor for simplicity.

5.2 Conditional Variance

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

$$\begin{gathered} \varepsilon_t = H_t^{1/2} v_t \\ H_t = D_t R_t D_t \\ D_t = diag(h_{1t}^{1/2}, h_{2t}^{1/2}, ..., h_{kt}^{1/2}) \\ h_{t+1} = W_1 + W_2 Out_t + A\varepsilon_t^{(2)} + B h_t \end{gathered} \tag{13}$$

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 kx1 vectors, A and B are diagonal kxk matrix of parameters. Hence for each series i, the corresponding volatility equation is:

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

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. 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 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 CCC-GARCH model by defining correlation dynamics as follows:

$$
\begin{aligned}
\mathbf{R}_t &= \mathbf{P}_t \mathbf{Q}_t \mathbf{P}_t \qquad (14)\\
\mathbf{P}_t &= diag(\mathbf{Q}_t)^{-1/2}\\
\mathbf{Q}_{t+1} &= (1-\delta_1-\delta_2)\overline{\mathbf{Q}} + \delta_1 \nu_t^* \nu_t^{*\prime} + \delta_2 \mathbf{Q}_t\\
\boldsymbol{\nu}_t^* &= diag(\mathbf{Q}_t)^{1/2} \boldsymbol{\nu}_t.\\
\nu_t &= \mathbf{D}_t^{-1} \varepsilon_t
\end{aligned}
$$

where $\overline{\mathbf{Q}}$ 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 reduces significantly the number of parameters to be estimated. δ_1 and δ_2 are non-negative 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 have a look at the network connections on a particular date: for example before and after a shock that affected 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. Gaussian three-step estimators are consistent and asymptotically normal. 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 not considering 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 are given 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:

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

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

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

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

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

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

Given that there are no volatility spillovers, we can estimate the conditional variance parameters $\Phi_i = \{w_{1i,}w_{2i,}a_i, b_i\}$ of each return series i univariately by maximizing: the following loglikelihood with respect to Φ_i:

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

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 volatilities and correlations of a CCC-GARCH model. However when estimating the correlation parameters of DCC and cDCC-GARCH models with 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 (14), resulting in smoother correlation estimates. For very high number of series, the estimate of the underlying correlation is close to being constant and equal to the long-run matrix. This might lead the researchers to assume that the conditional correlations in the data is constant over time. Composite likelihood method solves this problem by choosing small subsamples, evaluating the loglikelihood of these subsamples and taking an average over these loglikelihoods.[6]

If we would call $\Delta = \{\delta_1, \delta_2\}$ the correlation parameters, 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:

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

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 k series. These subsamples can be chosen as all subsequent series such as {{1,2},{2,3},...{k-1,k}}, or all possible bivariate combinations. It is also possible to choose trivariate subsamples as well. In our paper, we use all possible bivariate combinations. We also allow for different dynamics for the correlations between firms of the same sector, with parameters Δ_1 and of different sectors Δ_2. Hence if the chosen subsample comes from same sector the corresponding correlation parameter vector is Δ_1, if not, then it is Δ_2.

In the this stage we choose all bivariate combinations as subsamples and we construct the loglikelihood of these subsamples:

$$l_s = -\frac{1}{2}\sum_{t=2}^{T}\left(\log|\mathbf{R}_t| + \widehat{\nu}_t'\mathbf{R}_t^{-1}\widehat{\nu}_t\right) \tag{15}$$

[6] 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 $\Delta = [\Delta_1, \Delta_2]$:

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

After obtaining $\hat{\Delta}$, a forward recursion based on equation (14) 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, Sheppard, Shephard 2008).

7 Empirical Part

The network analysis as we described above can be applied in different cases to examine connectedness. In this section we apply this approach to study the connectedness between major firms in Russia.

7.1 Constant correlations

Constant correlation matrix $\hat{R}$ is estimated as correlations between standardized residuals in CCC-GARCH model. Using equation (5) we obtain an estimate of constant partial correlation matrix. Figure 2 displays histogram of ordinary correlations and partial correlation coefficients and borders of confidence interval for partial correlations around zero.[7] It can be seen that although there are no negative correlations, some partial correlations can be negative. However the majority of partial correlations are positive.

The network based on GGM is depicted on the Figure 3. Only significant partial correlations are used. Positive relationships between firms are indicated with solid lines while negative relationships are denoted by red dashed lines.

The graph in Figure 3 is crowded with links, so it is complicated to make any conclusions based on it. Some of the links are relatively weak, although they are significant. Hence, we can use some cutoff points in our network to make it more readable. If a cutoff point is relatively high, then only the strongest links will be plotted on the graph. Conversely, small cutoff point mean that we are interested in all significant edges. Using such kind off cutoff points helps us to make conclusions by looking at constructed graph. For example, Figure 4 shows the graph constructed for a cutoff point 0.1, where we can see strong connectedness

[7] In our work we test for significance of partial correlations with help of Fisher's Z transformation, i.e. we use $Z = \frac{1}{2}\ln(\frac{1+\rho_{i,j|.}}{1-\rho_{i,j|.}}) \sim N(0, \frac{1}{n-3})$, where n is the number of observations. The insignificant at 10% level partial correlations we set equal to zero. The most central firms in terms of connection with others and shock propagation are the same when we consider 5% significance level or when we use both significant and insignificant coefficients.

within some sectors such as Oil&Gas sector and Power sector. Moreover, we can note that in this graph there are clusters between some firms from Oil&Gas sector and Metal&Mining sector. Of course, it is just a suggestion based on the constructed graph by eliminating relatively small links, but we can check, whether it is true for the graph based on all significant partial correlations by calculating weights within sectors.

In the Table 2 we summarize network characteristics based on sectors. Firstly, we calculated the number of firms in each sector and the total number of links within sectors. It is not surprising that among the largest companies in Russia: 8 belong to the Oil&Gas sector and 7 - to Metal&Mining sector. Also the sum of weights within sectors was calculated. To compare calculated existence and strength of connectedness between all sectors these measures should be normalized by the number of possible connectedness within each sector. Columns $Av.edge$ and $Av.weights$ show normalized number of edges and sum of weights respectively.

Calculation of connectedness within sectors suggests that there are strong connectedness within Power sector while Oil&Gas sector is slightly less connected than Power and Financial sectors. Moreover, in terms of presence of connections, the Oils&Gas, Metal&Mining, Financial and Power sectors are similarly connected.

It is of interest to identify central players both in terms of connection with other firms and shock propagation in case of constant correlations model. We use centrality measurements discussed in Section 3. In Table 3 centrality measures are provided for the top twelve companies according to the Bonacich centrality (C^B), which represents top systemic contributors. There k is the number of neighbors of the companies, DC^{net}, DC^{abs}, DC^{+} are the degree centralities discussed in (7). We also calculate eigenvector centrality, EC, to show how far and how fast the shock of the firm can spread in the system. In order to compare different measures of connectedness we also use degree centrality (DC^{tune}) measure suggested by Opsahl, Agneessens, Skvoretz (2010) with tuning parameter $\alpha = 0.5$ 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 the Bonacich centrality. The order according to each measure is provided in the parentheses on the right side of the value.

The table shows that the most central firms in Russian Stock Market in terms of connection with others are Sberbank (SBER) and Lukoil (LKOH), while the most systemic risk contributors are FGC UES (FEES) and Gazprom (GAZP). It is interesting that the FGC UES (FEES) has less connections with others (e.g. $DC^{abs}$and DC^{tune} suggest it), but it has highest Bonacich and eigenvector centralities. It happens because FGC UES (FEES) has the strongest connection with the ROSSETI (RSTI), which makes propagation of the shock from FGC UES (FEES) faster and riskier for the system.

7.2 Dynamic correlations

CCC-GARCH model gives us a constant network of connections in Russian Stock Market. It is well known that Russia faced a number of problems during 2014, such as devaluation of ruble and trade sanctions imposed by European Union and Russian Federation, and 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, if we suggest that correlations between stock returns remained the same throughout all time. Hence, we are interested in examining how the connectedness between stocks changed over time, especially during the crisis. To do that we use 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 now can look at changes of macro characteristics of the networks. In Figure 5 we present changes in the number of significant edges and the average path length that we discussed in Section 3. We calculate average path length for the graph of absolute weights to look at the total connectedness of the network.

We can see that both the number of connections and the average path length change over time at the graph. Moreover, we see that in 2014 the former increases while the latter declines. This figure shows us that during the crisis the connectedness in Russian Stock Market strengthens. Similar results were obtained by Diebold and Yilmaz (2014) for U.S. stock market in the financial crisis 2007-2008.

In order to compare the conditions of the system over time in terms of systemic risk, we calculate the vulnerability of the system as the average of the Bonacich centrality measures of each firm. However, Bonacich centrality requires that all eigenvalues of adjacency matrices each time lay in unit circle. In Figure 6 we present the maximum absolute eigenvalues of adjacency matrices over time. As we can see, this assumption does not hold all the time. We can mark the days, when some eigenvalues are out of unit circle as the systemically most unstable days for the system. Indeed, the assumption is needed for convergence of the series in equations (10) and (11). When maximum absolute eigenvalue exceeds 1, the series diverge meaning that negative shock experienced by any firm can lead to a fall of the whole system. As can be seen from the Figure 6, the most considerably distressfull time for Russia of the end of 2014 and the first part of 2015 coincide with the period when eigenvalues of obtained adjacency matrices are outside the unit circle.

For the rest of the days, when eigenvalues were in the unit circle we calculate average and weighted average vulnerabilities of the system as it was described at the end of Section 4 and depict them in Figures 7 and 8 respectively. Both measures have similar dynamics and they show that vulnerability of the system changes over time rising during restless periods. The highest values are reached in the summer of 2012, that is at that time Russian stock market was considerably sensitive to the shock propagation. We should note that eigenvalues at these days reached their local maximum. Also it can be seen that before the marked risky days these measures were higher than usual indicating the coming of the most systemically unstable days.

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 for each of this periods respectively: 20 December 2013, 22 December 2014 and 22 December 2015. In Figures 9-11, we show the networks at each of these days using cutoff point equal to 0.12, i.e. edges with absolute weights less than 0.12 were not depicted. It should be noted again that we use cutoff point only for better visualization of the graph and we do not exclude small but significant edges when calculating different measures of the graph.

Now let us look at the centrality measures before, during and after the crisis. Here we use the same measures of centrality as in Table 3 in order to compare, which ones were central in terms of systemic risk and connections with others at different time. We provide these measures for three dates in Tables 4-6 only for the top twelve systemic contributors according to Bonacich centrality.

First of all, it should be noted that value of Bonacich centralities for all firms increased at the time of the crisis. It means that the system became more fragile at that time because of vulnerability of each firm. In terms of systemic risk Gazprom (GAZP) remained most crucial in all time slices, while FGC UES did not have central role during the crisis despite its importance before and after it. In terms of connection with other companies Surgutneftegas (SNGS) was most central during the crisis, while Sberbank (SBER) established the majority of the links in and after the crisis. Lukoil (LKOH) also was one of the most connected before and during the crisis, but became less crucial in 2015.

All three days in consideration above were chosen such that the assumption about the eigenvalues hold for calculating systemic risk contribution at these days. However, it might be useful to distinguish between days when this assumption holds and when it does not. In Table 7 we provide centrality measures for 24 December of 2014 when maximum absolute eigenvalue exceeded the unit circle and in the Figure 12 we show network of this day. Comparing these measures with the ones for 22 December, we can see that qualitative picture did not change a lot. The most central firms both in terms of connections and systemic risk remained on their top positions. Nevertheless, it can be seen that FGC UES became more influential in terms of systemic risk than it was before according to eigenvector centrality.

8 Further discussion

To justify our vulnerability measures empirically, we look at the government debt credit ratings scores given by major credit rating agencies, namely, Standard & Poors, Moody's and Fitch assessing the credibility of Russian economy in our data period from 1 December 2011 to 29 January 2016.[8] In Table 8, we present the time series data of the credit ratings and outlooks, rating scale to which each credit rating corresponds, rating scale with outlook to which each credit rating and outlook corresponds. Moreover we give the average and weighted average vulnerabilities and stability and weighted stability calculated as their inverses (one divided by vulnerability). The rating scale is calculated setting the worst possible credit score as 0 point and best as 24 points and allowing for increments of 1 points for each category. Rating scale is then adjusted for outlook, i.e. negative or positive, for which we gave half points, and if there is a "watch" assigned as well to the outlook (such as negative watch) we gave a quarter points. Hence if credit score is BBB, it corresponds to rating scale of 16, if the score is BBB with an outlook that is negative then rating scale with outlook is 15.50. If the score is BBB with an outlook that is negative watch, then the rating scale becomes 15.25.

When we look at Table 8, we see that there are two points where the vulnerability measures hit to infinity. These are the points when the maximum absolute eigenvalue is higher than 1, hence implying that the system is very unstable. Hence we set our stability measures equal to 0 in those points. The correlation of the rating scale with outlook with stability index is 0.33 while with the weighted stability index is 0.42. In Figure 13, we can see the comovement of the rating scale with outlook and the stability indices. If the stability indices would not hit to zero in two points, the correlations would have been higher.

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 Kalman smoother based on the estimated model. If this factor is a return from a certain market, we could proxy the index of this market by assuming an initial price of 100, and recovering the prices. In Figure 14, we plot the implied price index for the factor and also the Kalman smoothed estimate of the factor.

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. In Table 9, we look at the correlation of our estimated factor, and it's implied price index with the data we collected from possible observable external factors. We consider the indices and returns of SP500, MICEX, Rub/Usd exchange rate, Brent oil and HSI up to 2 lags. We convert the indices and returns of SP500, Brent oil and HSI from dollars to ruble. To account for the

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

risk consider the VIX index which is the implied volatility of the SP500, Morgan Stanley Composite index for Emerging Markets (MSCIEM) and for world markets (MSCIW). The latter two we converted from dollars to rubles. Finally, we also considered the Economic Policy Uncertainty Index for Russia.[9] This data is monthly, so we took the monthly mean and median of the factor, to check for correlation.

From Table 9, we can see that, there are many cases where the correlations are positive and significant. In particular, the factor is significantly positively correlated with the SP500 returns (in rubles), HSI returns (in rubles) and also with the Usd/Rub exchange rate returns, but not with the squares of these series. The factor is also significantly positively correlated with the MSCIEM and MSCIW indices. The monthly mean and median series of the factor is significantly positively correlated with the changes in the economic policy uncertainty. Finally, the implied prices of the factor is significantly positively correlated with the price levels and indices of many of the external factors we considered. Interestingly the correlation with VIX index is not significant, but the squared factor is correlated with the VIX index. On the other hand, the factor is significantly negatively correlated with the squared returns of Brent oil (in rubles) and with its two periods past values.

9 Conclusion

In this paper we mapped the most liquid and major firms in Russian Stock Market (MICEX) bringing together the ideas from financial econometrics, Gaussian graphical model and network analysis. More specifically, we derived partial correlations from the correlation estimates of constant conditional correlation (CCC) and consistent dynamic conditional correlation (DCC) GARCH models. Further using Gaussian graphical model approach, we derived the undirected weighted connections between the stocks. We examined the dynamics of some key network measures such as number of edges in graph and average path length and centrality. In addition, we distinguished centrality measures between two types: centrality as connectedness with others and centrality as importance for systemic risk. Given that we had connections with negative weights, these two centrality measures implied different results. We found that the most connected firms are Sberbank and Lukoil, while most central in terms of systemic risk are Gazprom and FGC UES.

On the other hand, using the Bonacich centralities of the stocks, we came up with two measures of vulnerability of the system: the first one is the average of Bonacich centralities, and the second - is the weighted average of Bonacich centralities. For the weights, we considered market capitalization of the stocks on each day. We defined the inverse of vulnerability

[9]Data source: http://www.policyuncertainty.com/

as the system stability index. It turns out that the stability indices discussed in our article represent comovement and positive correlation with the government debt credit ratings reported by major credit rating agencies, namely Standard & Poors, Moody's and Fitch.

Our article can be extended in various ways. First of all, one could include more stocks of financial companies and banks to 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 the system vulnerability would react to shocks introduced to these series.

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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.

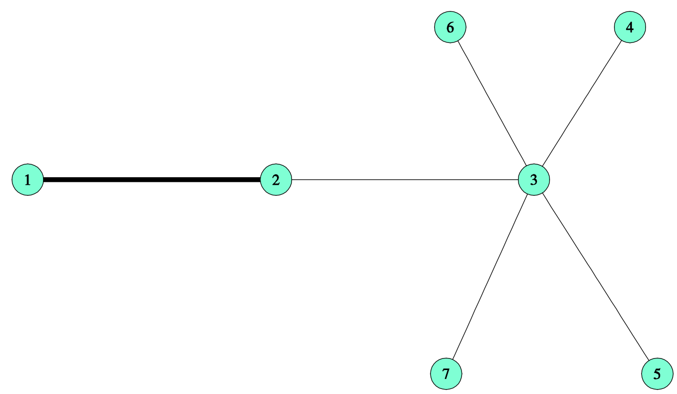

Figure 2: The figure shows histograms for ordinary correlations and partial correlations estimated with CCC-GARCH model. The vertical lines in partial correlation histogram indicate the 10% confidence interval according to Fishers's Z transformation test

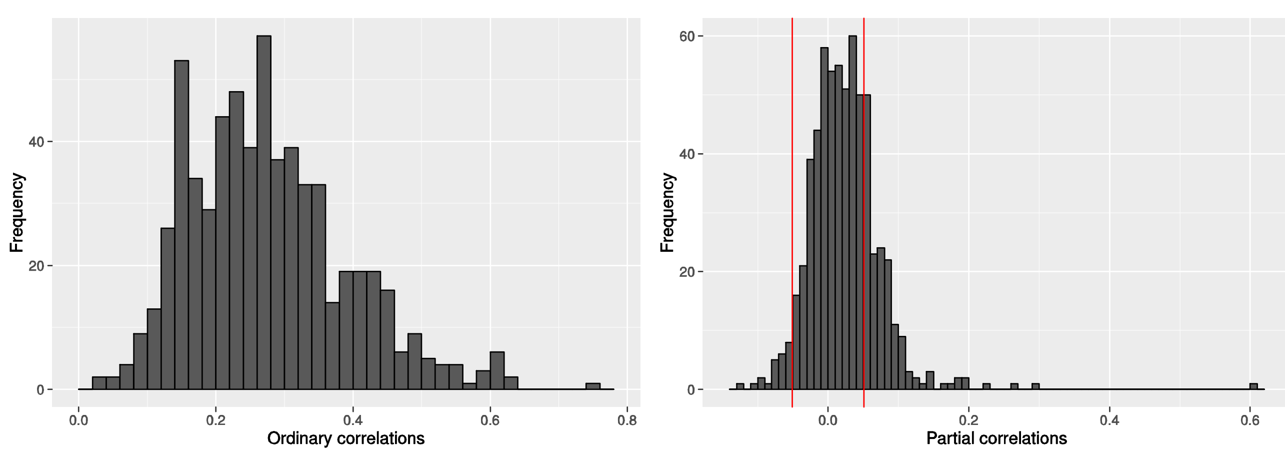

Figure 3: Network constructed using Gaussian Graphical Model. Network shows the bidirectional connectedness between major firms in Russian listed in MOEX. Nodes colored by the sectors. Solid lines between nodes denote positive conditional dependences between corresponding pairs while red dashed line denote negative relations. The thicker the line the stronger connection.

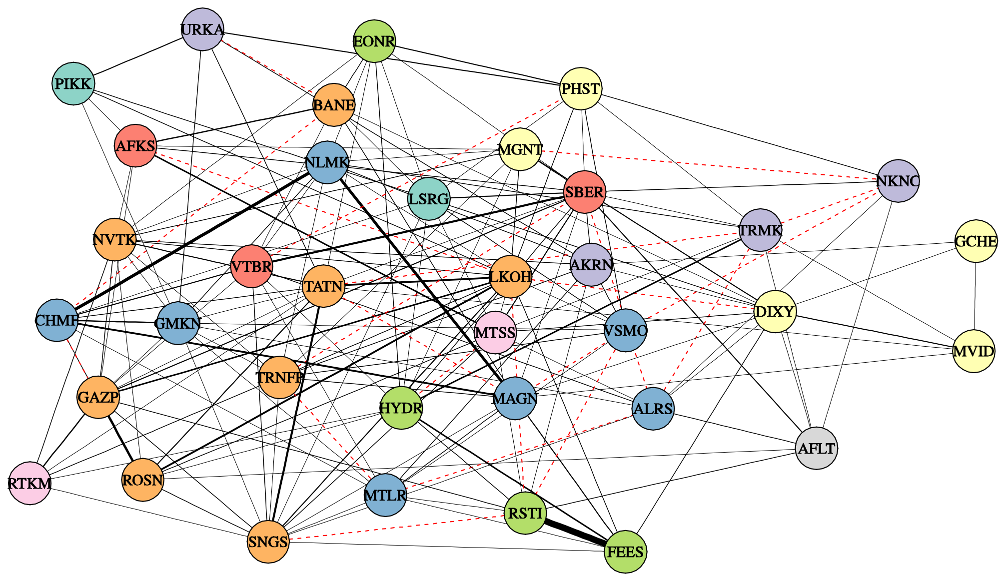

Figure 4: Network with cutoff point equal to 0.1

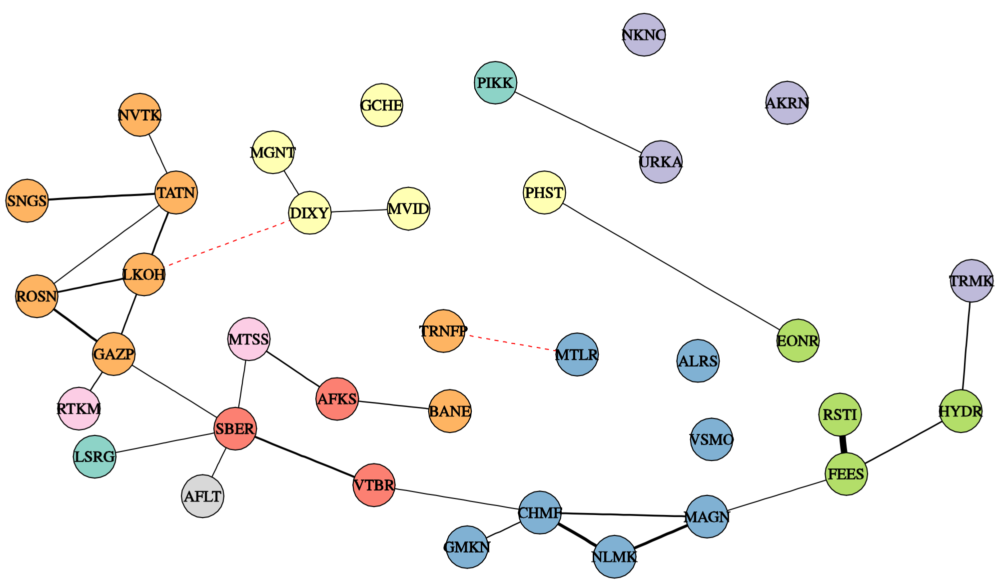

Figure 5: Left graph shows the number of significant edges during the time while the right graph presents the dynamic of average path length

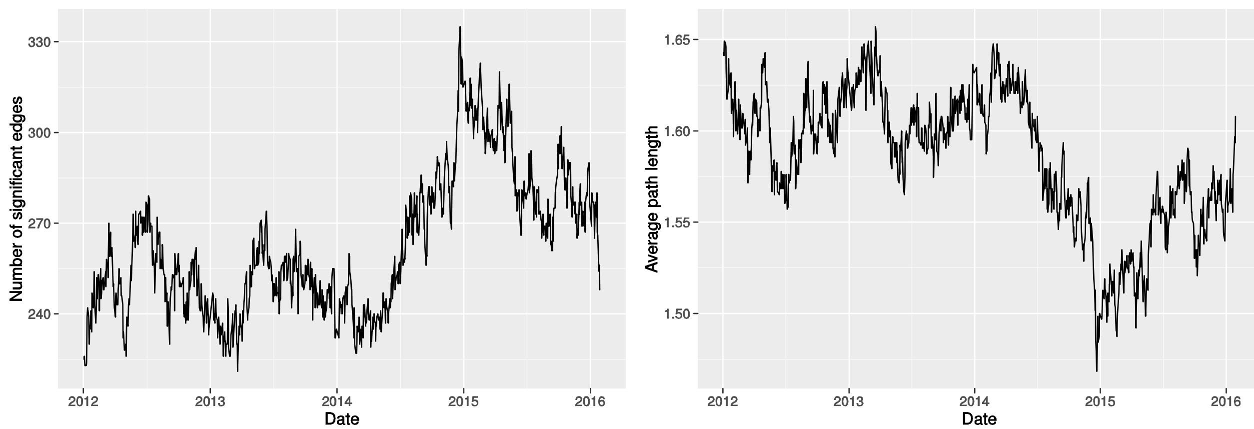

Figure 6: The maximum absolute eigenvalues of adjacency matrices over time.

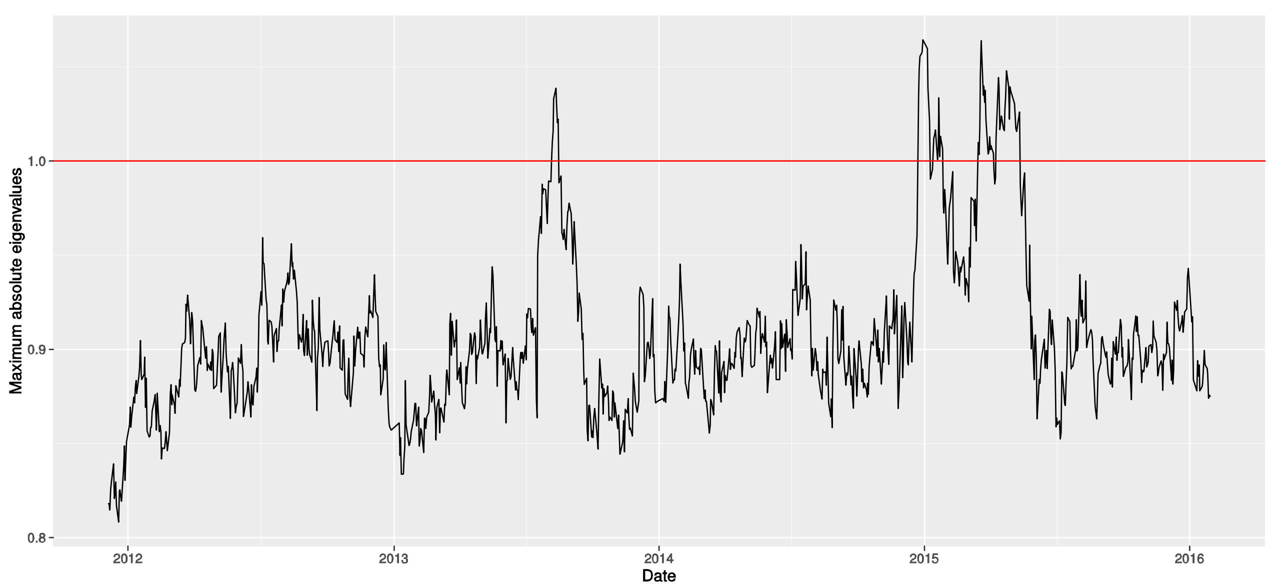

Figure 7: Average vulnerability of the system. It was calculated as the average of the Bonacich centralities of the nodes at each time

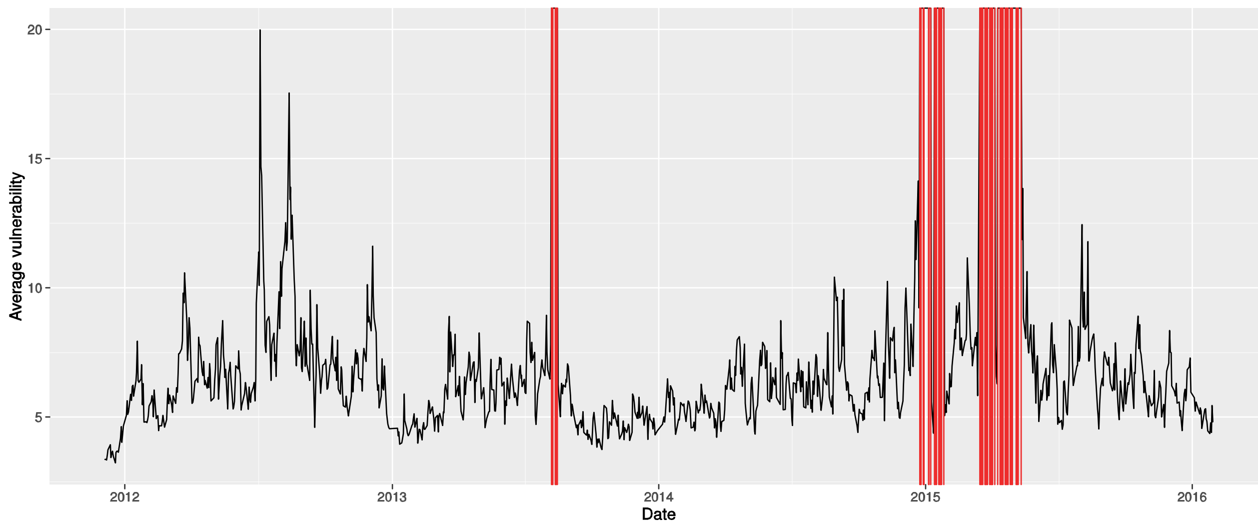

Figure 8: Weighted average vulnerability of the system. Weights were taken as the market capitalization weights among considered firms

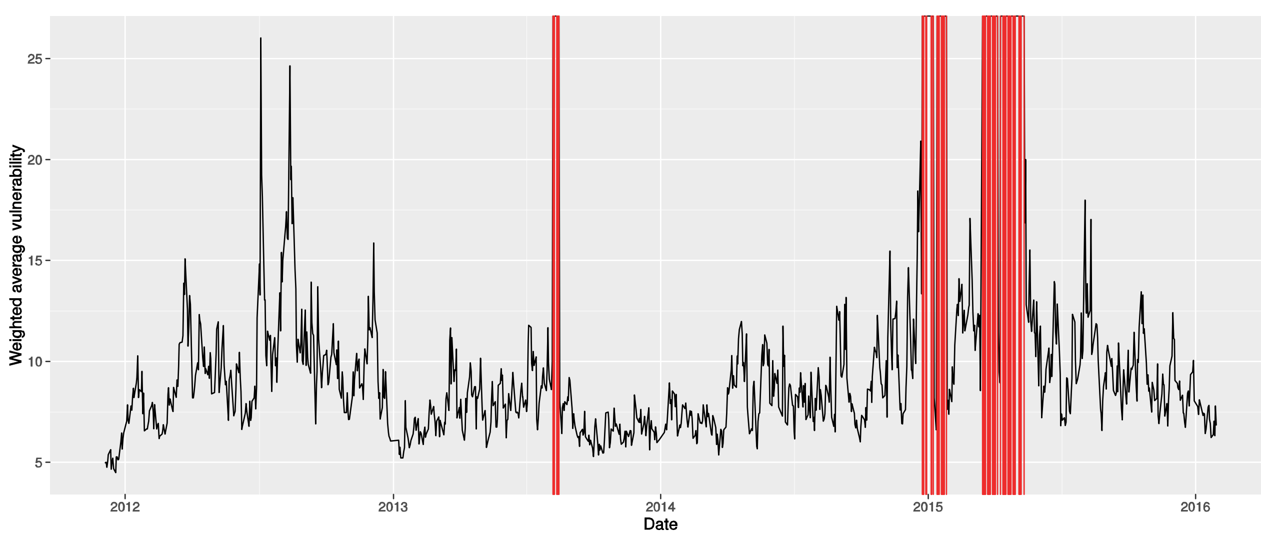

Figure 9: Network of 20 December 2013

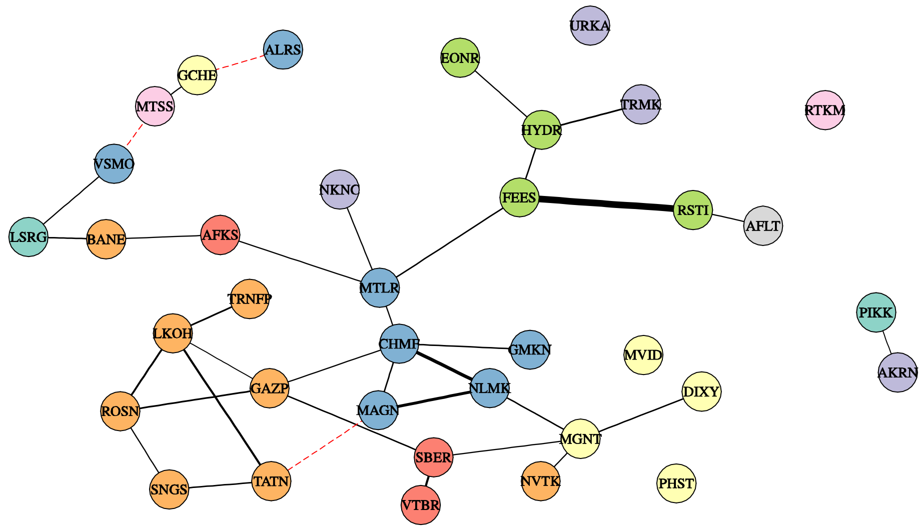

Figure 10: Network of 22 December 2014

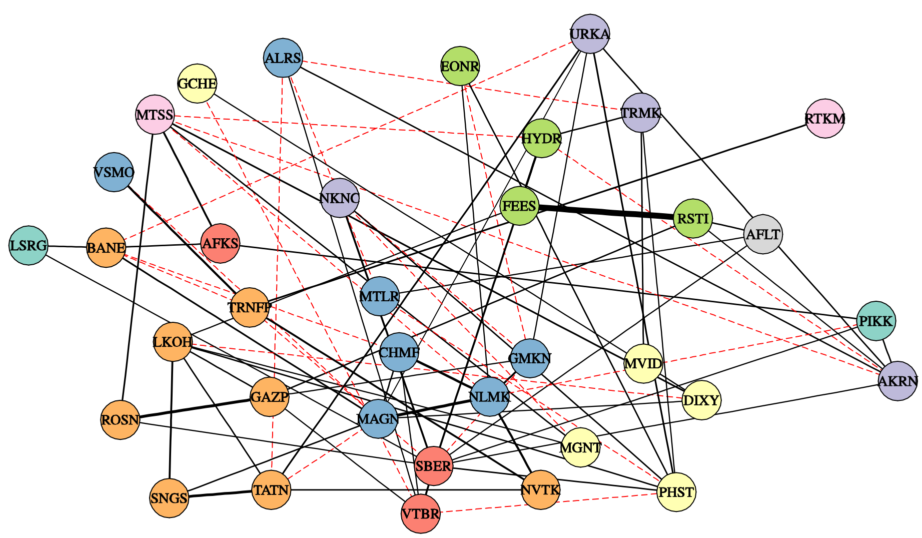

Figure 11: Network of 22 December 2015

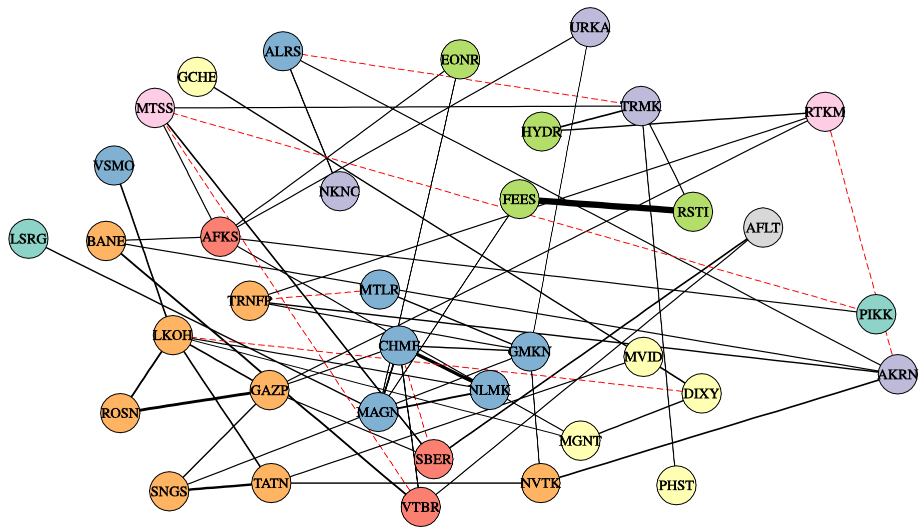

Figure 12: Network of 24 December 2014

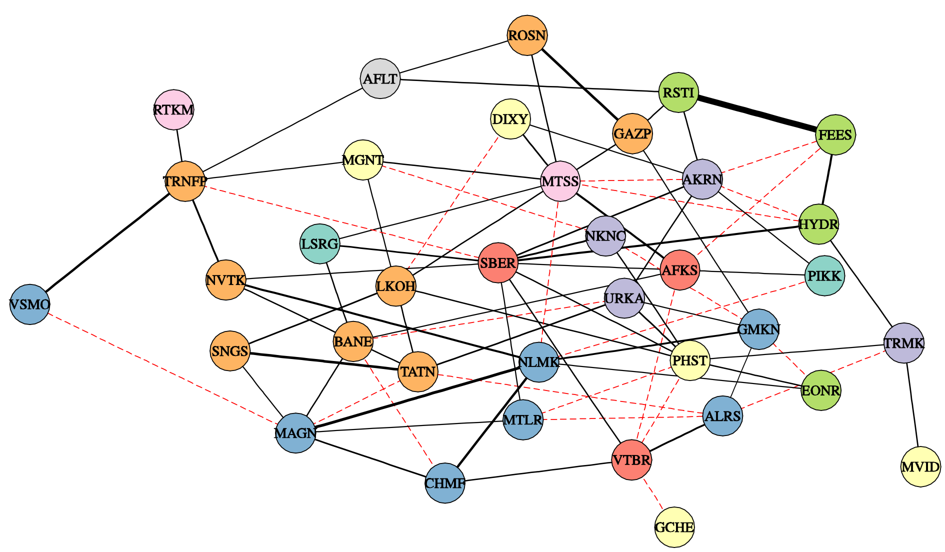

Figure 13: Rating scales with outlook (based on the credit ratings of major agencies on Russian economy) vs. the stability indices (calculated based on the vulnerability indices).

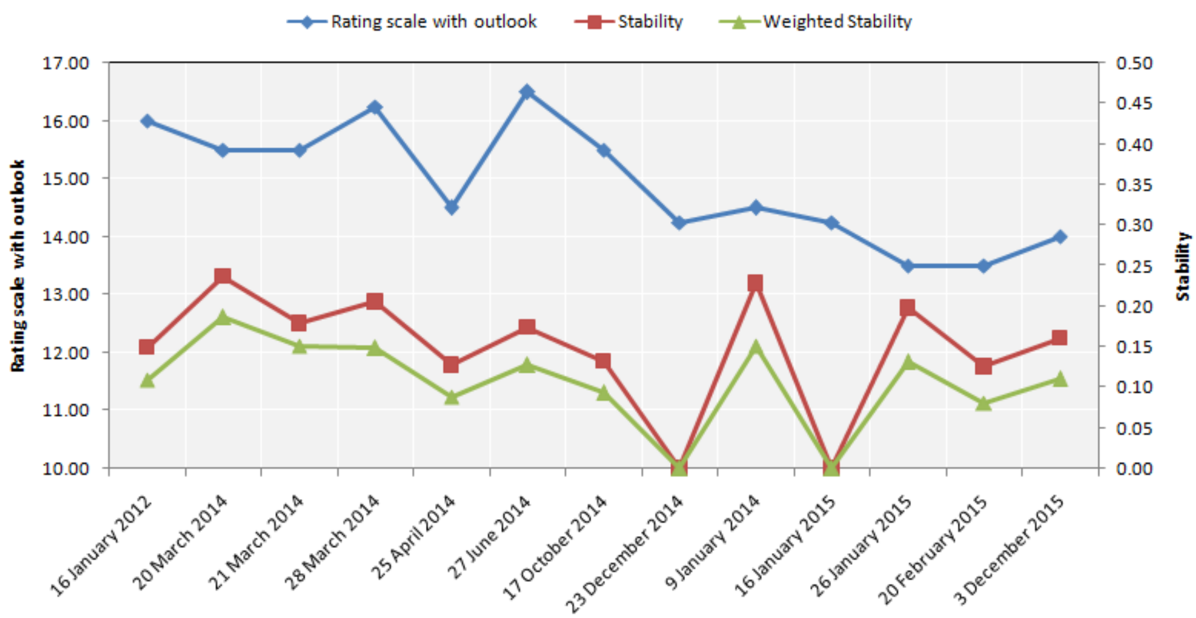

Figure 14: Kalman smoothed estimate of the unobservable factor and the implied price index for this factor.

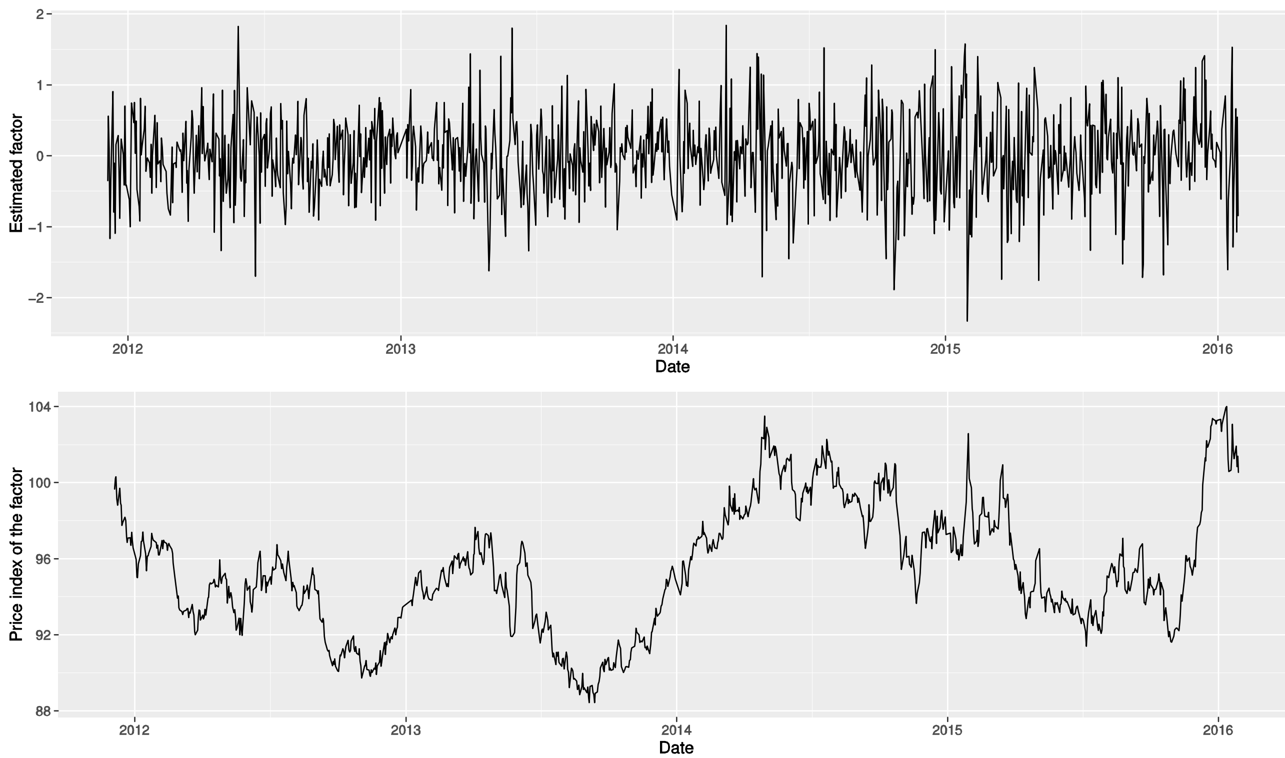

Table 1: Example

Node	k	DC	DC^{tune}
1	1	7	2.65
2	2	8	4
3	6	6	6

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

Table 2: Within sector calculations

Sector	# firms	# edges	sum of weights	# negative	Av.edges	Av.weights
O&G	8	17	1.9	0	0.6	0.068
M&M	7	13	1.2	2	0.62	0.057
CGS	5	4	0.344	0	0.4	0.034
PWR	4	4	0.938	0	0.667	0.156
CHM	4	2	0.022	1	0.333	0.004
FNL	3	2	0.27	0	0.667	0.09
C&D	2	1	0.087	0	1	0.087
TLC	2	1	0	0	0	0
TRN	1	0	0	0	-	-

Columns indicate from left to right, tickers of the sectors, number of edges within the sector, net sum of weights in the sector, number of negative edges within the sector, average number of edges equal to the number of edges divided by the number of possible edges within the sector, and average weights are the sum of weights divided by the number of all possible edges.

Table 3: Centrality Measures

	k	DC^{net}		DC^{abs}		DC^{+}		DC^{tune}		EC		EC^{abs}		C^{B}	
FEES	7	1.147	(10)	1.147	(10)	1.147	(5)	2.833	(20)	1.000	(1)	0.999	(2)	7.487	(1)
GAZP	12	1.200	(2)	1.200	(7)	1.200	(3)	3.795	(6)	0.895	(2)	0.889	(4)	7.337	(2)
NLMK	11	1.159	(8)	1.159	(8)	1.159	(4)	3.571	(7)	0.760	(5)	0.776	(9)	6.449	(3)
RSTI	10	0.856	(11)	1.223	(4)	1.040	(9)	3.497	(8)	0.877	(3)	1.000	(1)	6.378	(4)
LKOH	16	1.040	(6)	1.478	(1)	1.259	(2)	4.863	(2)	0.764	(4)	0.999	(3)	6.326	(5)
SNGS	15	1.082	(5)	1.204	(5)	1.143	(6)	4.249	(3)	0.724	(6)	0.869	(6)	6.111	(6)
TATN	14	0.927	(7)	1.279	(3)	1.103	(7)	4.232	(4)	0.693	(8)	0.886	(5)	5.764	(7)
SBER	17	1.202	(1)	1.464	(2)	1.333	(1)	4.988	(1)	0.635	(11)	0.731	(11)	5.737	(8)
CHMF	10	0.863	(10)	1.152	(9)	1.007	(10)	3.394	(9)	0.694	(7)	0.815	(8)	5.705	(9)
MAGN	12	0.897	(8)	1.201	(6)	1.049	(8)	3.797	(5)	0.650	(9)	0.832	(7)	5.378	(10)
ROSN	9	0.771	(15)	0.957	(11)	0.864	(11)	2.934	(16)	0.638	(10)	0.774	(10)	5.185	(11)
NVTK	12	0.863	(9)	0.863	(16)	0.863	(12)	3.218	(12)	0.555	(12)	0.542	(15)	4.763	(12)

This table shows calculated different centrality measures for top twelve companies according to Bonacich centrality in the case of constant model. Here k is the number of adjacencies of the node; DC^{net}, DC^{abs}, DC^{+} are net degree centrality, degree centrality of adjacency matrix with absolute values, positive degree centrality measures respectively; DC^{tune} is tuned degree centrality with $\alpha = 0.5$; EC and EC^{abs} are eigenvector centrality for adjacency matrix and adjacency matrix with absolute values and C^{B} is Bonacich centrality with $\beta = 1$.

Table 4: Centrality Measures. 20.12.2013

	k	DC^{net}		DC^{abs}		DC^{+}		DC^{tune}		EC		EC^{abs}		C^{B}	
FEES	12	1.102	(6)	1.646	(5)	1.374	(3)	4.444	(13)	1.000	(1)	1.000	(1)	9.501	(1)
GAZP	14	1.132	(4)	1.407	(14)	1.269	(9)	4.438	(14)	0.796	(3)	0.709	(13)	8.974	(2)
LKOH	16	1.130	(5)	1.675	(4)	1.402	(2)	5.177	(6)	0.709	(5)	0.866	(4)	8.252	(3)
SNGS	20	1.165	(2)	1.820	(1)	1.492	(1)	6.032	(1)	0.715	(4)	0.882	(3)	8.209	(4)
NLMK	12	1.168	(1)	1.472	(12)	1.320	(6)	4.203	(19)	0.647	(8)	0.743	(11)	7.954	(5)
RSTI	13	0.853	(14)	1.607	(6)	1.230	(11)	4.571	(11)	0.870	(2)	0.944	(2)	7.914	(6)
SBER	17	1.133	(3)	1.567	(8)	1.350	(4)	5.162	(7)	0.629	(10)	0.721	(12)	7.576	(7)
CHMF	12	1.014	(8)	1.478	(11)	1.246	(10)	4.211	(17)	0.614	(11)	0.768	(8)	7.512	(8)
ROSN	13	0.888	(11)	1.267	(18)	1.077	(15)	4.058	(22)	0.665	(7)	0.696	(14)	7.382	(9)
HYDR	18	1.050	(7)	1.524	(10)	1.287	(8)	5.237	(5)	0.672	(6)	0.743	(10)	7.227	(10)
MAGN	19	0.950	(10)	1.699	(3)	1.324	(5)	5.681	(3)	0.581	(12)	0.850	(5)	7.009	(11)
TATN	17	0.726	(17)	1.554	(9)	1.140	(14)	5.139	(8)	0.636	(9)	0.779	(7)	6.965	(12)

Table 5: Centrality Measures. 22.12.2014

	k	DC^{net}		DC^{abs}		DC^{+}		DC^{tune}		EC		EC^{abs}		C^{B}	
GAZP	16	1.407	(3)	1.702	(23)	1.555	(10)	5.219	(25)	1.000	(1)	0.621	(22)	28.245	(1)
LKOH	26	1.131	(7)	2.709	(2)	1.920	(2)	8.393	(2)	0.931	(2)	0.959	(2)	25.928	(2)
NVTK	20	1.366	(4)	1.880	(14)	1.623	(7)	6.132	(11)	0.887	(3)	0.687	(14)	25.544	(3)
SNGS	16	1.485	(2)	1.590	(27)	1.537	(12)	5.043	(28)	0.862	(4)	0.621	(23)	25.084	(4)
TATN	21	0.893	(13)	2.259	(8)	1.576	(9)	6.887	(7)	0.845	(5)	0.833	(8)	23.614	(5)
ROSN	18	0.829	(16)	1.732	(19)	1.281	(20)	5.583	(18)	0.820	(6)	0.637	(18)	23.041	(6)
NLMK	19	1.159	(6)	2.295	(7)	1.727	(4)	6.604	(9)	0.799	(7)	0.871	(6)	22.705	(7)
FEES	18	1.181	(5)	2.036	(10)	1.609	(8)	6.054	(13)	0.709	(8)	0.747	(11)	21.016	(8)
SBER	25	1.493	(1)	2.893	(1)	2.193	(1)	8.505	(1)	0.596	(12)	1.000	(1)	18.760	(9)
MTSS	22	0.999	(8)	2.357	(6)	1.678	(6)	7.201	(6)	0.606	(11)	0.855	(7)	17.639	(10)
CHMF	18	0.831	(15)	1.787	(17)	1.309	(17)	5.671	(16)	0.613	(9)	0.648	(16)	17.314	(11)
GMKN	20	0.725	(21)	2.003	(11)	1.364	(15)	6.329	(10)	0.608	(10)	0.723	(12)	16.590	(12)

Table 6: Centrality Measures. 22.12.2015

	k	DC^{net}		DC^{abs}		DC^{+}		DC^{tune}		EC		EC^{abs}		C^{B}	
GAZP	16	1.518	(1)	1.787	(5)	1.652	(1)	5.347	(11)	1.000	(1)	0.968	(4)	13.597	(1)
FEES	12	1.055	(7)	1.676	(13)	1.366	(6)	4.485	(21)	0.833	(2)	0.946	(7)	10.696	(2)
RSTI	15	1.060	(6)	1.854	(2)	1.457	(3)	5.273	(14)	0.829	(3)	1.000	(1)	10.591	(3)
LKOH	13	1.080	(4)	1.690	(12)	1.385	(5)	4.687	(19)	0.731	(4)	0.847	(15)	9.875	(4)
SNGS	18	1.078	(5)	1.821	(3)	1.450	(4)	5.726	(4)	0.675	(7)	0.976	(3)	9.340	(5)
ROSN	16	0.776	(19)	1.648	(18)	1.212	(17)	5.135	(16)	0.721	(5)	0.871	(12)	9.294	(6)
TATN	18	0.844	(15)	1.784	(6)	1.314	(8)	5.666	(6)	0.683	(6)	0.948	(6)	9.205	(7)
NVTK	14	1.165	(2)	1.322	(23)	1.244	(14)	4.303	(25)	0.632	(8)	0.664	(25)	9.169	(8)
SBER	22	1.114	(3)	1.980	(1)	1.547	(2)	6.601	(1)	0.602	(9)	0.979	(2)	8.547	(9)
MTSS	18	0.851	(13)	1.702	(11)	1.277	(12)	5.536	(8)	0.527	(11)	0.903	(9)	7.297	(10)
HYDR	13	0.860	(12)	1.287	(26)	1.074	(22)	4.091	(28)	0.539	(10)	0.661	(26)	7.195	(11)
GMKN	17	0.815	(17)	1.661	(15)	1.238	(15)	5.315	(12)	0.486	(13)	0.833	(16)	6.984	(12)

Table 7: Centrality Measures. 24.12.2014

	k	DC^{net}		DC^{abs}		DC^{+}		DC^{tune}		EC		EC^{abs}	
GAZP	17	1.401	(2)	1.833	(20)	1.617	(5)	5.582	(20)	1.000	(1)	0.640	(19)
LKOH	23	1.179	(6)	2.538	(3)	1.859	(2)	7.640	(3)	0.916	(2)	0.862	(3)
FEES	20	1.191	(5)	2.243	(7)	1.717	(3)	6.698	(8)	0.897	(3)	0.790	(6)
NVTK	20	1.275	(4)	1.908	(16)	1.592	(7)	6.178	(13)	0.831	(4)	0.651	(18)
TATN	22	0.852	(9)	2.294	(6)	1.573	(9)	7.104	(5)	0.803	(5)	0.783	(7)
SNGS	14	1.363	(3)	1.466	(29)	1.414	(14)	4.531	(31)	0.787	(6)	0.526	(27)
ROSN	19	0.824	(11)	1.904	(18)	1.364	(16)	6.015	(16)	0.778	(7)	0.656	(16)
NLMK	18	1.143	(7)	2.187	(9)	1.665	(4)	6.275	(12)	0.744	(8)	0.763	(9)
RSTI	16	0.766	(17)	2.066	(13)	1.416	(13)	5.750	(19)	0.693	(9)	0.744	(11)
SBER	24	1.539	(1)	2.991	(1)	2.265	(1)	8.472	(1)	0.645	(10)	1.000	(1)
HYDR	18	0.703	(21)	1.905	(17)	1.304	(19)	5.856	(17)	0.577	(11)	0.674	(15)
MGNT	14	0.779	(16)	1.397	(33)	1.088	(27)	4.422	(32)	0.541	(12)	0.487	(34)

Table 8: Credit ratings history

Agencies	Credit rating	Outlook	Dates	R.S.	R.S., out	Avg. Vuln.	W. Avg. Vuln.	Stability	W. Stab.
Fitch	BBB	stable	16.01.2012	16.00	16.00	6.71	9.19	0.15	0.11
S&P	BBB	negative	20.03.2014	16.00	15.50	4.22	5.37	0.24	0.19
Fitch	BBB	negative	21.03.2014	16.00	15.50	5.58	6.63	0.18	0.15
Moody's	Baa1	neg. watch	28.03.2014	17.00	16.25	4.87	6.74	0.21	0.15
S&P	BBB-	negative	25.04.2014	15.00	14.50	7.83	11.36	0.13	0.09
Moody's	Baa1	negative	27.06.2014	17.00	16.50	5.73	7.83	0.17	0.13
Moody's	Baa2	negative	17.10.2014	16.00	15.50	7.59	10.70	0.13	0.09
S&P	BBB-	neg. watch	23.12.2014	15.00	14.25	Inf	Inf	0	0
Fitch	BBB-	negative	09.01.2015	15.00	14.50	4.38	6.61	0.23	0.15
Moody's	Baa3	neg. watch	16.01.2015	15.00	14.25	Inf	Inf	0	0
S&P	BB+	negative	26.01.2015	14.00	13.50	5.05	7.62	0.20	0.13
Moody's	Ba1	negative	20.02.2015	14.00	13.50	7.95	12.32	0.13	0.08
Moody's	Ba1	stable	03.12.2015	14.00	14.00	6.22	9.05	0.16	0.11

Table 9: Pearson correlations between the smoothed factor and external data.

Series	Corr(.,factor)	Series	Corr(.,factor)
SP500 returns (in rub)	0.0862 (0.0053)	SP500 (in rub) sq.	0.0286 (0.3555)
MICEX returns	−0.0000 (0.9991)	MICEX sq.	−0.0300 (0.3327)
USD/RUB returns	0.0932 (0.0026)	USD/RUB sq.	0.0018 (0.9549)
BRENT returns (in rub)	−0.0123 (0.6910)	BRENT (in rub) sq.	−0.0772 (0.0127)
HSI returns (in rub)	0.1114 (0.0003)	HSI returns (in rub) sq.	−0.0005 (0.9878)
SP500 returns (in rub) (-1)	0.0059 (0.8481)	SP500 returns (in rub) (-1) sq.	−0.0101 (0.7437)
MICEX returns (-1)	−0.0655 (0.0345)	MICEX returns (-1) sq.	0.0240 (0.4382)
USD/RUB returns (-1)	0.0113 (0.7147)	USD/RUB returns (-1) sq.	0.0262 (0.3984)
BRENT returns (in rub) (-1)	−0.0464 (0.1342)	BRENT returns (in rub) (-1) sq.	−0.0013 (0.9659)
HSI returns (in rub) (-1)	−0.0102 (0.7431)	HSI returns (in rub) (-1) sq.	0.0343 (0.2686)
SP500 returns (in rub) (-2)	0.0217 (0.4848)	SP500 returns (in rub) (-2) sq.	−0.0295 (0.3414)
MICEX returns (-2)	0.0541 (0.0813)	MICEX returns (-2) sq.	0.0407 (0.1897)
USD/RUB returns (-2)	0.0450 (0.1469)	USD/RUB returns (-2) sq.	−0.0397 (0.2007)
BRENT returns (in rub) (-2)	0.0038 (0.9028)	BRENT returns (in rub) (-2) sq.	−0.0660 (0.0333)
HSI returns (in rub) (-2)	0.0341 (0.2716)	HSI returns (in rub) (-2) sq.	−0.0329 (0.2896)
VIX	−0.0292 (0.3461)	VIX (-1)	−0.0219 (0.4810)
VIX vs squared factor	0.1181 (0.0001)	VIX vs squared factor (-1)	0.1135 (0.0002)
MSCIEM* (in rub)	0.0939 (0.0029)	MSCIW* (in rub)	0.0892 (0.0077)
Unc. ind. vs monthly mean f.	0.1142 (0.4298)	Ch. in unc. ind. vs monthly mean f.	0.2305 (0.1111)
Unc. ind. vs monthly med. f.	0.1969 (0.1705)	Ch. in unc. ind. vs monthly med. f.	0.2648 (0.0660)
SP500 ind. (rub) vs factor price	0.3136 (0.0000)	USD/RUB levels vs factor price	0.2901 (0.0000)
MICEX index vs factor price	0.0507 (0.1015)	BRENT price (rub) vs factor price	0.2152 (0.0000)
HSI index vs factor price	0.0405 (0.1914)		
MSCIEM* index (rub) vs factor price	0.3284 (0.0000)	MSCIW* index (rub) vs factor price	0.3394 (0.0000)

Table 10: Stocks listed in MICEX with corresponding sector information

Ticker	Name	S. Index	Sector
AFKS	AFK SISTEMA	FNL	Financial
AFLT	JSC "AEROFLOT"	TRN	Transport
AKRN	Acron	CHM	Chemicals
ALRS	AC "ALROSA"	M&M	Metals and mining
BANE	OAO ANK "Bashneft"	O&G	Oil and gas
CHMF	Severstal	M&M	Metals and mining
DIXY	DIXY Group	CGS	Consumer goods and services
EONR	OAO "E.ON Rossiya"	PWR	Electricity, utilities
FEES	"FGC UES" JSC	PWR	Electricity, utilities
GAZP	GAZPROM	O&G	Oil and gas
GCHE	PJSC "Cherkizovo Group"	CGS	Consumer goods and services
GMKN	"OJSC" MMC "NORILSK NICKEL"	M&M	Metals and mining
HYDR	JSC "RusHydro"	PWR	Electricity, utilities
LKOH	OAO "LUKOIL"	O&G	Oil and gas
LSRG	OJSC LSR Group	C&D	Construction and development
MAGN	OJSC "MMK"	M&M	Metals and mining
MGNT	OJSC "Magnit"	CGS	Consumer goods and services
MTLR	Mechel OAO	M&M	Metals and mining
MTSS	MTS OJSC	TLC	Telecommunications
MVID	Open Joint-Stock Company "M.video"	CGS	Consumer goods and services
NKNC	PJSC "Nizhnekamskneftekhim"	CHM	Chemicals
NLMK	NLMK	M&M	Metals and mining
NVTK	JSC "NOVATEK"	O&G	Oil and gas
PHST	JSC "Pharmstandard"	CGS	Consumer goods and services
PIKK	"PIK Group"	C&D	Construction and development
ROSN	Rosneft	O&G	Oil and gas
RSTI	PJSC "ROSSETI"	PWR	Electricity, utilities
RTKM	Rostelecom	TLC	Telecommunications
SBER	Sberbank	FNL	Financial
SNGS	Surgutneftegas	O&G	Oil and gas
TATN	TATNEFT	O&G	Oil and gas
TRMK	TMK	CHM	Chemicals
TRNFP	Transneft Pref.	O&G	Oil and gas
URKA	Uralkali	CHM	Chemicals
VSMO	VSMPO-AVISMA Corporation	M&M	Metals and mining
VTBR	JSC VTB Bank	FNL	Financial