Analysis of Financial Network Topological Dynamics of the Russian Stock Market from 2012 to 2019

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Abstract. In this paper we study some properties of the Russian stock market with the application of network approaches and data-driven science. Complex networks theory allows us to construct and analyse topological network structures of the market. Among the important information which is possible to acquire from it is the relationships between stocks returns with the analysis of hidden information and market dynamics. This paper is focused on the analysis of the market network dynamics over time. We construct market networks for 75 consecutive overlapping 250-day periods to analyze the dynamics of the structural properties of the market rank-correlation-based network. Degree distribution and maximum clique size are considered as the important structural characteristics of the market network. In our opinion these parameters are the essential graph attributes and give insight into Russian financial market structure.

1. Introduction

Network models can be used to represent interactions of agents in financial or economic systems. The financial network was defined in [1]. In it nodes are various organizations (i.e. banks, firms, investors, etc.) linked in a network. The links are projections of financial interdependencies (i.e. cross-ownership of financial assets, interorganizational debts / liabilities, social relations between board members, etc.). An iconic example of a banking network is built in [2]. It illustrates how systemic risk can emerge from financial interdependencies between banks. It should be noted that a majority of real-world networks are ones which are constantly changing.

Networks based on financial markets may have a large amount of nodes (assets) and edges (interconnections). A simplification of initial networks is possible by excluding excess data. Among the methods of filtering of financial networks are based on the implication of hierarchical trees (HT) [3,4], planar maximally filtered graphs (PMFG) [5], asset graph (AG) [6], and partial correlation network [7–9]. Moreover, another possible method of network filtering was created by Mantegna [3] and used in [10]. In it hierarchical structures of financial networks are examined with the use of minimum spanning tree method.

Recent years have seen an increased interest in the studies which apply and develop an approach which is based on market graphs. Related papers include empirical studies based on real market data and explore various structural properties and attributes of market graphs, such as maximum cliques, maximum independent sets, degree distribution, clustering, the complexity of the market graph [11–15]. Firstly considered in [16], an edge is inserted between two vertices into the filtered market graph if the corresponding value of chosen correlation coefficient is
higher than a given threshold. Some features of different financial markets are studied in articles [12, 17–21]. Not only correlation can measure market graphs. More possible measures are given in [8, 17, 22–25].

In this paper, we study network based on Russian financial market using some methods of complex network theory. The structure of Russian financial market network can be investigated with the usage of complex network analysis and SNA methods based on the correlation relationship between the components of the system (assets). Various major financial markets have been successfully studied by network analysis methods.

These include US market [26–28], Germany [4, 29], EU [30–32], Italy [33, 34]. Among the focus of researchers are some developing markets such as Chinese [12, 28, 35, 36], Brazil [37, 38], Korea [39], Russia [19], and Mexico [40, 41]. Furthermore, some in some articles global markets are examined using network approach [42, 43].

It turned out that the network analysis is capable of both finding the importance of individual companies using different centrality measures [44, 44] and analyzing systemic risks and stability of financial market based on the topological properties of networks [45–47]. In order to find main influencers on banking behaviours in the global environment systemic risk contagion has been analyzed in [48, 49]. The paper [50] which studied European markets had shown that European markets are also exposed to systemic risks. Thus systemic risk analysis based with the use of network approach may help to provide useful implications for market regulations.

During the past ten years, the Russian economy suffered a series of shocks such as the sharp fall of oil prices in 2014 and the sanctions imposed by governments of European Union countries and the United States. Both shocks brought widespread and long-lasting negative impacts and led to a slowdown in the Russian economy growth. These dramatic events have been reflected in the Russian stock market behavior. Thus, it is important to study the properties of the Russian stock market by employing the data-driven science and network approaches.

This paper is focused on the Russian financial analysis of the market network dynamics over time. We construct market networks for 75 consecutive overlapping 250-day periods to analyze the dynamics of the structural properties of the market network. Degree distribution and maximum clique size are considered as the important structural characteristics of the market network. In our opinion these parameters are essential graph attributes and give insight into the news flow internal structure.

The paper is organized as follows. First, Section 2 describes the data and method used to construct networks. Section 3 presents market network properties using market graph approach proposed in [11, 16]. Section 4 examines hierarchical structures of the Russian stock network using HT, MST, PMFG and AG approaches and compares them with findings of the paper [28]. Finally, conclusions are presented in Section 5.

Studying the behavior of the stock markets may allow regulators to make them more stable. It should be noted that in addition to methods based on the use of the market graph, in the study of financial markets one can use machine learning methods, in particular neural networks, evolutionary computing, among many others [51–56].

2. Definitions and Notations

2.1. Link, degree distribution and local clustering coefficient

Social network analysis (SNA) can be used to describe social relations in the context of graph theory. SNA uses objects (e.g., individuals, groups, organizations and URLs, etc.) of a network as nodes, and any kind of relationships between them as links (e.g., association, friendship, co-authorship, etc.) [57], [58], [59].

Firstly, some basic definitions from graph theory should be introduced. Let \( G = (V, E) \) be an undirected graph with \( n \) vertices \( V \) and a set of edges \( E = \{(i, j) : i, j \in V\} \).
The degree of a vertex indicates the number of edges connected to it. For any integer number \( k \) we can calculate the number of vertices \( n(k) \) whose degrees are equal to \( k \) and then get the probability that a vertex in the graph has the degree \( k \) as \( P(k) = n(k)/n \), with \( n \) being the overall number of vertices. The function \( P(k) \) is referred to as the degree distribution of the graph, which is an important characteristic of graphs.

It should be noted that many real graphs based on different fields (Internet, economics and finance, telecommunications, medicine and biology, sociology) exhibit a degree distribution which follows the power law model \([60],[61],[62],[63],[64],[65]\). Basically, it shows that the probability of vertex having degree \( k \) asymptotically follows

\[
P(k) \propto k^{-\gamma}, \text{ or } \log P(k) \propto -\gamma \log k,
\]

which indicates that this function maintains linear dependence on a logarithmic plot. Scale-free property is an important characteristic of this model. It means that despite its development and growth over time, the fractal structure of a network remains constant \([66]\).

The local clustering coefficient for node \( i \) is defined as \( C_i = \frac{E_i}{\binom{k_i}{2}} \), where \( E_i \) is the number of links connecting the immediate neighbors of \( i \), and \( k_i \) being the degree of \( i \). Furthermore, the average clustering coefficient in a network is defined as the average of all clustering coefficients of each node in it. Knowing the value of average clustering coefficient we may measure the strength of connectivity within the network. \( C(k) \) is defined as the average clustering coefficient of all nodes with degree \( k \). It is known that for a vast majority of real networks \( C(k) \) follows the power law model

\[
C(k) \propto k^{-\beta},
\]

where it is common for the exponent \( \beta \) to lie between 1 and 2 (see e.g. \([67],[68],[69],[70],[71],[72]\)).

2.2. Cliques and independent sets

The graph \( G = (V,E) \) is considered connected if for any two vertices from \( V \) there exists a path connecting them. If the graph is disconnected, it may be divided into a number of connected subgraphs (which would be the connected components of \( G \)).

Let \( G(S) \) be the subgraph produced from \( S \) for a subset \( S \subseteq V \). The number \( C \subseteq V \) would be called a clique if \( G(C) \) is a complete graph. The task of finding the largest clique in a graph can be solved.

A subset \( I \subseteq V \) is called an independent set if the subgraph \( G(I) \) has no edges. The task of finding the largest independent set in a graph is similar to the maximum clique problem of the complementary graph \( \overline{G}(V,\overline{E}) \). Since the maximum clique in \( \overline{G} \) is a maximum independent set in \( G \), we can easily reduce the maximum clique and maximum independent set problems to each other.

It may be said that independent sets contain objects that diverge from any other object in the set. This is an important characteristic which may be further applied. Knowing the maximum clique gives us the highest possible size of sets of so-called related items, whilst the largest independent in contrast can provide us with the size of the largest possible set of different objects in the network.

The maximum clique problem exists in practical applications of numerous fields. Numerous practical problems can be directly described as a maximum clique problem and, moreover, in many cases it can be reduced to the maximum clique problem. Its real-world applications appear in signal processing, classification theory, coding theory, computer vision, economics, finance, information retrieval, signal transmission theory, aligning DNA and protein sequences, social network analysis, and other particular areas. Some of the applications may be found in \([19,73–81]\), among many others.
3. Data and Methodology

3.1. Data Description

In terms of GDP (PPP) Russia and its developing economy is the sixth among other countries in the world. Both RTS and the Moscow Stock Exchange indices are the major indicators of the Russian stock market. The RTS, however, is calculated in dollars, while the MICEX is in rubles. The open source data of daily prices for all companies for the period from 10/01/2012 to 10/03/2019 (1800 trading days) was downloaded from Yahoo Finance. Likewise, data on the MICEX index was downloaded from the Moscow Stock Exchange considering the same period. Our research examines data for 191 companies in total, among which 32 companies are included in the MICEX index.

Some companies that are parts of the MICEX index (e.g. CBOM, DSKY, FIVE, LNTA, MOEX, POLY, RNFT, RUAL, SFIN) were still not included in our dataset. This is due to a short trading history (approx. 2-3 years) which is insufficient to build a relevant model. Also, we excluded non-liquid assets whose prices did not change during 250 trading days from our data set. Therefore, after both selection and cleaning processes, we include 191 stocks traded on IMOEX in our dataset from five industry sectors.

4. Empirical Results

4.1. Market Network Construction

In order for correlation $\rho_{ij}$ to be calculated for a pair of stocks, it is required to use time series of prices (Adj Close) $P_i(t)$ for each company $s_i$ at the same time period $t$. Next, to smooth the oscillations we use log returns $Y_i(t)$ of a company $s_i$ in a time period $[t-\Delta t,t]$ defined by

$$Y_i(t) = \ln P_i(t) - \ln P_i(t - \Delta t),$$

where $\Delta t = 1$ for daily prices. Next the Pearson correlation coefficient is calculated for each pair of companies $s_i$ and $s_j$ as follows

$$r_{ij} = \frac{\text{cov}(Y_i, Y_j)}{\sigma_{Y_i} \sigma_{Y_j}} = \frac{\langle Y_i Y_j \rangle - \langle Y_i \rangle \langle Y_j \rangle}{\sqrt{(\langle Y_i^2 \rangle - \langle Y_i \rangle^2)(\langle Y_j^2 \rangle - \langle Y_j \rangle^2)}}$$

where $\text{cov}(Y_i, Y_j)$ is covariance of variables, $\sigma_{Y_i}, \sigma_{Y_j}$ standard deviations, $\langle \cdot \rangle$ denotes the average value. The Spearman correlation coefficient is calculated as

$$r_{ij}^S = \frac{\text{cov}(\text{rank}(Y_i), \text{rank}(Y_j))}{\sigma_{\text{rank}(Y_i)} \sigma_{\text{rank}(Y_j)}},$$

where $r^S$ denotes the usual Pearson correlation coefficient, but applied to the rank variables, $\text{cov}(\text{rank}(Y_i), \text{rank}(Y_j))$ is the covariance of the rank variables, $\sigma_{\text{rank}(Y_i)}$ and $\sigma_{\text{rank}(Y_j)}$ are the standard deviations of the rank variables.

The sign correlation of Fechner is defined by

$$r_{ij}^F = \langle \text{sign}(Y_i - \langle Y_i \rangle) \text{sign}(Y_j - \langle Y_j \rangle) \rangle$$

where

$$\text{sign}(x) = \begin{cases} 1, & x \geq 0 \\ -1, & x < 0 \end{cases}$$
Expression for Kendall’s rank coefficient is

\[ r_{K}^{ij} = \frac{2}{n(n-1)} \sum_{l<m} \text{sign}(Y_{il} - Y_{im}) \text{sign}(Y_{jl} - Y_{jm}), \]

After we get the values of the correlation coefficient for all pairs of companies we are able to construct the \(N \times N = 191 \times 191\) distance matrix where distance is defined using this equation

\[ d_{ij} = \sqrt{2(1 - \rho_{ij})}, \quad (5) \]

where \(\rho_{ij}\) is one of possible correlation coefficient \((r_{ij}, r_{ij}^{S}, r_{ij}^{F}, r_{ij}^{K})\).

Using Eq. (5) we calculate distance matrices for each window. It should be noted that distance provides us only positive values, which is better than simply using correlations for further computations. All vertices in the network are fixed between windows. However, edges vary in each rolling window as the distances change. So, we may average all distance matrices from all rolling windows of the study periods. The statistical properties of the network are examined in this section.

The network with edges corresponding to distance may be simplified by filtering edges with small weights. The market graph can be constructed based on using a threshold approach: for some fixed threshold value \(\theta\) we remove edges whose weights are bigger than \(\theta\) and keep the remaining edges. In other words, we filter network edges as follows:

\[ e_{ij} = \begin{cases} 1, & d_{ij} < \theta, \\ 0, & d_{ij} \geq \theta. \end{cases} \]

It is known that for the same values of variables the values of the Spearman correlation coefficient will always be slightly larger than the values of the Kendall rank correlation coefficient, while the significance level will be the same or the Kendall correlation coefficient will be slightly larger. Therefore, in order to obtain similar network density indicators, it is necessary to use different threshold values.

4.2. Basic network properties

In this paper, we observe and analyse topological properties of the IMOEX network using the dynamic approach from the paper [28]. We acquire a set of rolling windows of size \(L = 250\) to meet the requirement \((L/N > 1)\), where the number of stocks is \(N = 191\). In total, 75 rolling windows were created based on IMOEX. Further, we calculated the log returns for all IMOEX stocks by using Eq. (1) followed by calculation of the Pearson correlation coefficient matrix for all windows over the period from 10/01/2012 to 10/03/2019 using Eq. (2).

One could notice that the values of correlations between assets that are traded in the Russian stock market are low. One of the explanations could be the low liquidity of most stocks in IMOEX. Furthermore, it can be easily verified that even highest liquidity shares possess low correlations. So network density for a network created from these stocks has similar dependency from \(\theta\) as the whole IMOEX network.

To study the dynamics of the market graph we divide the 1800-day trading days interval into 75 consecutive overlapping 250-day periods. The dates corresponding to each period are presented in Table 1.

4.3. Degree distribution

A network of correlations can be determined for each of the correlation coefficients (Kendal, Pearson, Spearman, Fechner). Therefore, Fig. 1 shows the graph densities for cutoff levels \(\theta = 1.2\) for the coefficients \(r, r^{S}\) and \(\theta = 1.1\) for the coefficients \(r^{F}, r^{K}\).
Table 1. Periods IDs and their starting and ending dates.

| Period | Start          | End            |
|--------|----------------|----------------|
| 1      | 10.01.2012     | 10.01.2013     |
| 2      | 10.02.2012     | 10.02.2013     |
| 3      | 10.03.2012     | 10.03.2013     |
| .      | .              | .              |
| 73     | 10.01.2018     | 10.01.2019     |
| 74     | 10.02.2018     | 10.02.2019     |
| 75     | 10.03.2018     | 10.03.2019     |

The rank correlation coefficients are less sensitive to outliers than the Pearson correlation coefficient. In fig. 1 one can see a sharp jump (March 2014) in the density of the network constructed with the use of the Pearson correlation coefficient. A careful analysis allows us to conclude that this is due to the presence of the only one outlier that occurred on March 3, 2014. Rank measures are more resistant to anomalous values in the data and the graphs generated by them are more stable. It can be seen that the graph densities obtained using the three different rank correlation coefficients are quite similar. We will analyze the properties of networks constructed on the basis of the Spearman coefficient \( r_S \) in the subsequent discussion.

Edge densities for different thresholds from 1.1 to 1.2 are shown in Fig. 2. As can be seen from the graph, the highest density of market graphs was observed at the beginning of the analyzed period, and then its smooth decline began. The political crisis of March 2014 led to a slight increase in density, but then the edge densities decrease, which indicates the disintegration of the Russian financial market.

We investigate the degree distributions for the IMOEX networks filtered with different values of \( \theta \). The degree distributions are noisy for both small values of \( \theta \) and large ones (Fig. 3). The log-binning procedure was used to build the regression and calculate the power law exponent, since the use of linear approximation (linear-binning) significantly underestimates the exponent \( \gamma \). The evolution of the market graph shows that the degree distribution is not stable. Before the crisis and in the crisis of 2014, the \( \gamma \) exponent is less than 1. It should be noted that the degree exponent has its lowest value in the financial crisis of 2014. After the crisis, \( \gamma \) takes values greater than 2, which corresponds to a scale-free network. Note that for many real networks the values of the degree exponent lie between 2 and 3.

Fig. 4 presents the degree distributions (in the log-log scale) for some instances of the market graph corresponding to different time periods. A negative tilt angle indicates that the network...
is scale-free, in which a small part of the vertices has greater degrees, and most of the vertices have smaller degrees. It can be seen that these plots can be well approximated by straight lines (except for the crisis year 2014), which means that they represent the power-law distribution.

Fig. 5 shows the dynamics of the local clustering coefficient from January, 2012 to March, 2019. As you can see, the local clustering coefficient is very unstable and even takes negative values. Accordingly, in most cases it is not necessary to mention the presence of a power law of distribution for the local clustering coefficient. For $\theta = 1.1$ it was not at all possible to estimate this parameter after 2017 due to the insufficient number of points.

4.4. The evolution of the size of the maximum clique

The second problem the paper addresses is the analysis of the maximum clique size evolution on graphs during 7 years from January 10, 2012 till March 10, 2019 (87 months). It follows from the definition of the clique that it is a set of fully interconnected vertices, and therefore each stock that refers to the clique is firmly connected with all the other stocks in this clique.

Since the size of the maximum clique represents the largest possible group of similar objects, it can be considered as an important characteristic of the market graph.

In this paper one of the variants of the Bron–Kerbosh algorithm proposed in [82] was employed...
Figure 4. The degree distribution of the market network for $\theta = 1.15$

Figure 5. Dynamics of the local clustering coefficient $\beta$

to find the explicit maximum clique. The Bron–Kerbosh algorithm recursively solves sub-problems detailed by three sets of vertices:

- the vertices that must be embodied in the given clique,
- the vertices that should be excluded from the clique, and
- some remaining vertices whose status remains unknown.

This algorithm is proved to be competent and powerful for appropriately sparse networks. Note
that our market networks are very sparse. An accurate description of the algorithm is presented in the paper [83].

The dynamics of the maximum clique size for the marker network are shown in Fig. 6. It can be seen that the size of the maximum clique attained its largest value at the beginning of the period under review. We also note that during the 2014 crisis, an increase in the maximum clique size was observed.

Table 4.4 presents List of companies in maximum clique for 7 years.

| year | ticker | size | number |
|------|--------|------|--------|
| 2012 | AFLT AKRN APTK BLNG CHMF FEES GAZP HYDR IRAO MAGN MSNG MTLR MTLRP NLMK NVTK OGKB RASP RSTI RTKM SBER SBERP SNGS TATN VTBR | 24 | 1 |
| 2013 | CHMF GAZP GMRN LKOH MAGN MTLR MTLRP NLMK NVTK ROSN SBER SBERP SNGS TATN TATNP | 14 | 2 |
| 2014 | AFLT BSPB CHMF FEES GAZP IRAO KMAZ LKOH MAGN MFON MSNG MTSS NLMK NVTK OGKB RASP RBCM ROSN RSTI RTKM RTKMP SBER SBERP SNGS SNGSP | 18 | 13 |
| 2015 | FEES GAZP HYDR IRGZ LKOH MGNT MTSS NVTK ROSN RSTI SBER SBERP SNGS TATN | 9 | 6 |
| 2016 | GAZP LKOH ROSN SBER SBERP TATN VTBR | 6 | 2 |
| 2017 | GAZP LKOH ROSN SBER SBERP SNGS TATN | 7 | 1 |
| 2018 | LSNGP MTLR MTLRP OGKB SBER SBERP TGKA VTBR | 6 | 3 |

* Energy Industrial, Financial Service, Telecommunication Services

Table 4 presents the characteristics of the market graph during the period under consideration. The results show that company marker networks are all in all sparse. On the contrary, the sizes of independent sets in each period of time are large and almost constant over time. It implies that interconnections of a large amount of companies are not presented in the news flow.

5. Conclusion
We analyzed the topological properties of market graphs based on the returns of Russian financial assets. The characteristics of market graphs based on Pearson’s sample correlation matrices
### Table 3. Company Names

| Sector       | Ticker | Name                         |
|--------------|--------|------------------------------|
| Energy       | GAZP   | Gazprom                      |
|              | HYDR   | RusHydro                     |
|              | IRAO   | Inter RAO                    |
|              | IRGZ   | Irkutskenergo                |
|              | LKOH   | Lukoil                       |
|              | MSNG   | Mosenergo                    |
|              | OGKB   | Wholesale Generation Company No. 2 |
|              | ROSN   | Rosneft                      |
|              | RSTI   | Rosseti                      |
|              | SNGS   | Surgutneftegaz               |
|              | TATN   | Tatneft                      |
|              | TGKA   | Territorial Generation Company No. 1 |
|              | NVTK   | Novatek                      |
|              | LSGP   | Lenenergo                    |
| Financials   | SBERP  | Sberbank of Russia           |
|              | VTBR   | VTB Bank                     |
|              | BSPB   | Bank Saint-Petersburg        |
| Service      | APTK   | Pharmacy Chain 36.6          |
|              | MGNT   | Magnet                       |
| Industrials  | AKRN   | Akron                        |
|              | CHMF   | Severstal                    |
|              | GMKN   | Nornickel                    |
|              | MAGN   | Magnitogorsk Iron and Steel Works |
|              | AFLT   | Aeroflot                     |
|              | MTLR   | Mechel                       |
|              | NLMK   | NLMK Group                   |
|              | BLNG   | Belon                        |
|              | KAMAZ  | KamAZ                        |
|              | RASP   | Raspakskaya                  |
| Telecommunications Services | MTSS  | MTS                          |
|              | RTKMP  | Rostelecom                   |
|              | MFON   | Megafon                      |
|              | RBCM   | RBK                          |

### Table 4. Characteristics of the market graph ($\theta = 1.15$)

| Period | Edge density | Maximum clique | Maximum independent set | Diameter | Degree exponent $\gamma$ | Local clustering coefficient $\beta$ |
|--------|--------------|----------------|--------------------------|----------|--------------------------|-------------------------------------|
| 2012   | 0.048        | 24             | 144                      | 5        | 0.47                     | -0.13                               |
| 2013   | 0.021        | 14             | 158                      | 5        | 0.52                     | -0.45                               |
| 2014   | 0.034        | 18             | 150                      | 5        | 0.54                     | -0.34                               |
| 2015   | 0.012        | 9              | 159                      | 6        | 1.08                     | 0.36                                |
| 2016   | 0.003        | 6              | 172                      | 4        | 1.64                     | -1.10                               |
| 2017   | 0.006        | 7              | 167                      | 6        | 1.42                     | 0.79                                |
| 2018   | 0.006        | 6              | 164                      | 6        | 1.18                     | 0.72                                |
are sensitive to anomalous values. More stable and consistent results are obtained using rank correlation coefficients (Spearman, Kendal, Fechner). In this article, we chose a procedure based on Spearman’s rank correlations between returns to study the topological properties of the financial network. We used the rolling window procedure to study trends in the properties of a market graph such as the graph density, clique number, as well as the law of the distribution obtained from degrees of vertices. Network metrics smoothly change over time, reflecting the presence of long-term trends in the strength of the relationship between the stock returns of Russian companies.

The clique number and the stability of a subset of companies included in the clique can be used as characteristics of the homogeneity of the financial market. We found a tendency to weaken the correlation between returns and reduce the number of companies from the maximum clique. This allows us to come to conclusion that the Russian market is becoming more heterogeneous. We can distinguish a stable subset of securities, the returns of which demonstrate a strong correlation among themselves in all periods under consideration. The maximum clique is formed around only a few of the largest Russian companies in oil and gas industry or banking sector. The upward trend in the size of the maximum clique is manifested during the period of foreign policy and financial turbulence, which may be associated with an increase in the share of systematic risk in the total volatility. A diversified portfolio consists of shares of energy and industrial enterprises not included in the maximum clique.

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