

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

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Outline

- 1 Introduction
- 2 Network construction
- 3 Constant model
- 4 Dynamic model
- 5 Conclusion

Introduction

Systemic risk

- The financial crisis of 2008 called for better understanding of the risks
- Specifically, systemic risk - "the risk of a cascading failure in the financial sector"
- "Too interconnected to fail"
- **Purpose** is to find the most interconnected and threatening firms in Russian economy and measure systemic risk



Connections

- Firms can be connected in different ways
 - i.e. trading or loan relations - in firm's balance sheets
- However, it's not high-frequency data
- Connections between stock returns is a proxy of true unobservable links
- **Data** is stock returns of firms listed in MICEX:
 - returns of 36 companies based on EOD stock prices
 - data period: 01.12.2011 - 29.01.2016
- We bring together the ideas from financial econometrics and network theory

Network construction

Gaussian Graphical Model

- Consider m.r.v. $X = \{X_1, \dots, X_n\}$ of stock returns
- We want to construct graph $G = (V, E)$, where
set of **V**ertices $V = \{1, \dots, n\}$ represents set of firms
set of **E**dges is set of connections between them
- GGM measures dependence as partial correlation between each pair of nodes
- Partial correlation, $\rho_{i,j|\cdot}$, between X_i and X_j shows linear dependence between them excluding influence of the rest of components of X
- If $\rho_{i,j|\cdot} = 0 \Rightarrow X_i$ and X_j are independent $\Rightarrow (i, j) \notin E$

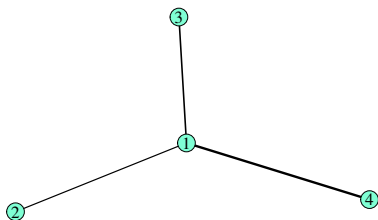
[more](#)

Network

The network can be represented with adjacency matrix with weights $w_{i,j} = \rho_{i,j}$.

$$A = I + P$$

$$A = \begin{bmatrix} 0 & 0.3 & 0.4 & 0.6 \\ 0.3 & 0 & 0.2 & 0 \\ 0.4 & 0.2 & 0 & 0 \\ 0.6 & 0 & 0 & 0 \end{bmatrix}$$



Estimation

Partial correlation matrix P can be calculated as follows:

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

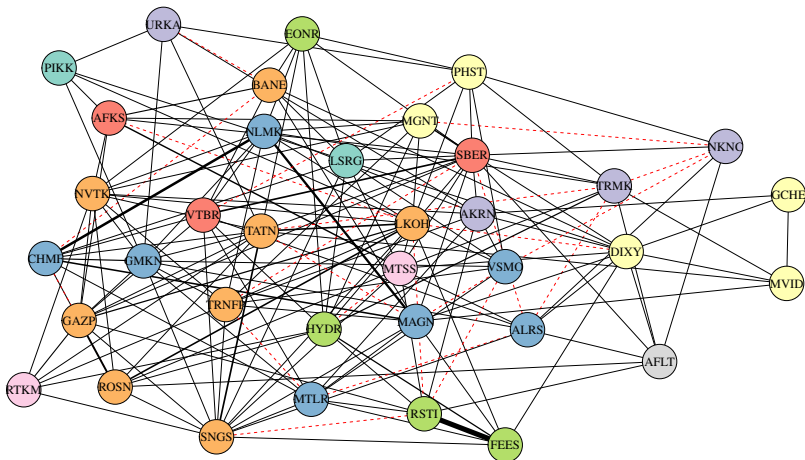
where $K = \Omega^{-1}$ or $K = R^{-1}$

To estimate \hat{R} we use financial econometrics models:

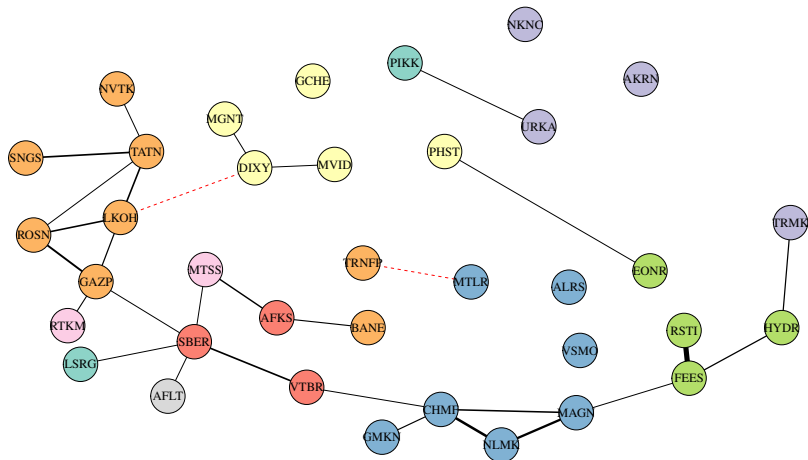
- CCC-GARCH model $\hat{R} \Rightarrow \hat{P}$
- cDCC-GARCH model $\hat{R}_t \Rightarrow \hat{P}_t$

Constant model

CCC-GARCH Network



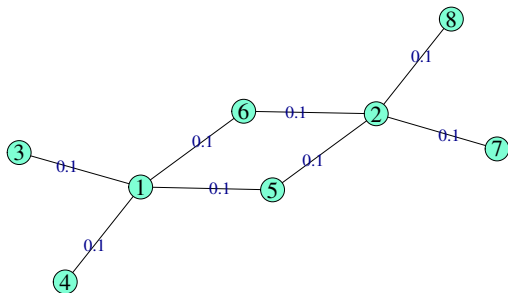
CCC-GARCH Network, Threshold=0.1



Degree centrality

For weighted graph *degree centrality* is the sum of the weights of his edges

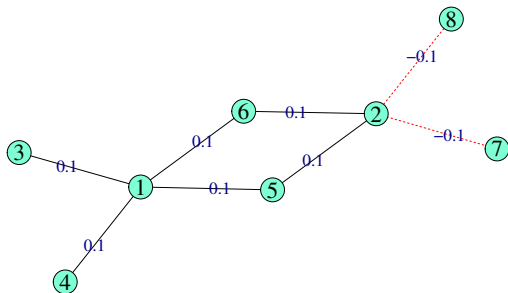
$$DC = \sum_{j=1}^n w_{i,j} = \sum_{j=1}^n a_{i,j}, \quad DC = A \cdot \mathbf{1}$$



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Degree centrality(II)

In terms of the graph with both positive and negative connections it is possible to distinguish DC as follows

- in terms of connections with others

$$DC_i^{abs} = \sum_{j=1}^n |a_{i,j}|, \quad DC^{abs} = abs(A) \cdot 1$$

- in terms of systemic risk

$$DC_i^{net} = \sum_{j=1}^n a_{i,j}, \quad DC^{net} = A \cdot 1$$

Eigenvector centrality

- *Eigenvector centrality* measures centrality based on the neighbours' centrality

$$\lambda C^e(i) = \sum_{j=1}^n w_{i,j} C^e(j) = \sum_{j=1}^n a_{i,j} C^e(j)$$

$$\lambda C^e = AC^e$$

λ is proportional parameter = (maximum) eigenvalue of A

- *Bonacich centrality* shows how central node in terms of systemic risk

$$C^B(1) = A \cdot 1 + A^2 \cdot 1 + A^3 \cdot 1 + \dots = (I - A)^{-1} \cdot 1 - 1$$

Measuring fall

- Let e be the negative shock experienced by some firm, i.e. by firm 1 $\Rightarrow e = (s, 0, \dots, 0)^T$,

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- k -th-order effect $A^k e$

Measuring fall

- Let e be the negative shock experienced by some firm, i.e. by firm 1 $\Rightarrow e = (s, 0, \dots, 0)^T$,
- First-order effect Ae
- Second-order effect A^2e
- ...
- k -th-order effect $A^k e$
- The total effect on the system

$$e + Ae + A^2e + \dots + A^k e + \dots = \sum_{k=0}^{\infty} A^k e = (I - A)^{-1} e$$

$T = (I - A)^{-1} \Rightarrow Te$ is total effect of the shock e on all others

Centrality measures of CCC model

| | 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) |

Dynamic model

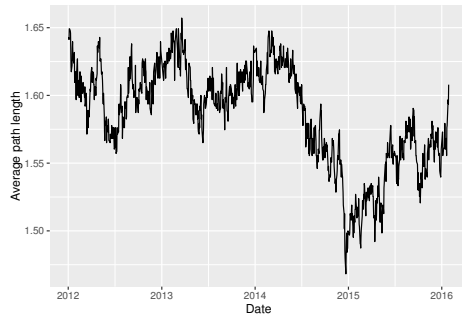
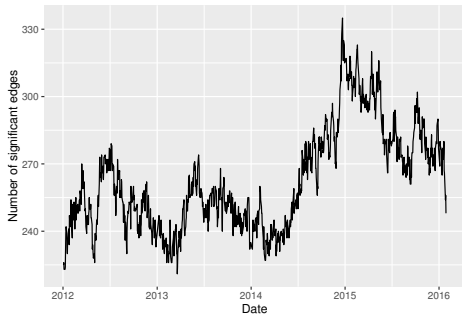
Macro characteristics

- The number of edges in the graph
- *The average path length* is the average shortest path between any two nodes

The average number of steps needed to shock propagate from one node to another

- The more the number of the edges, the less is the average path length
- Average vulnerability is the average of the Bonacich centralities
Sensitivity of the network to the negative shocks

Number of edges and average path length in dynamic



Vulnerability measure

Bonacich centrality shows how central node in terms of systemic risk

$$C^B(1) = A \cdot 1 + A^2 \cdot 1 + A^3 \cdot 1 + \dots = (I - A)^{-1} \cdot 1 - 1$$

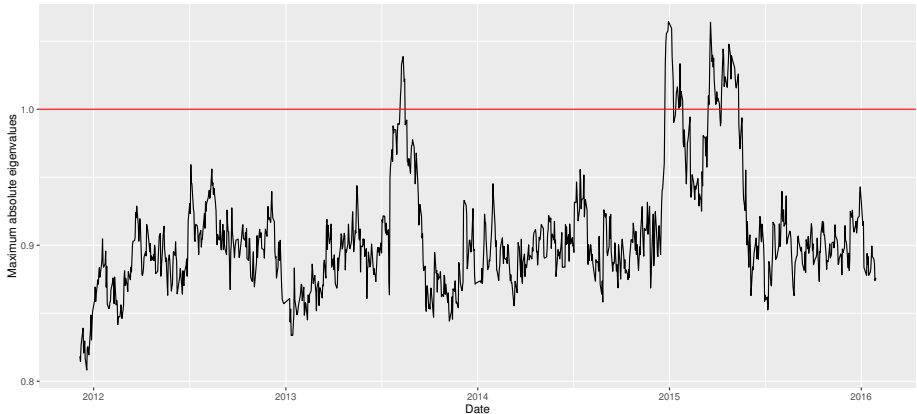
Assumption: all eigenvalues inside the unit circle

Average vulnerability is the average of Bonacich centralities of all firms

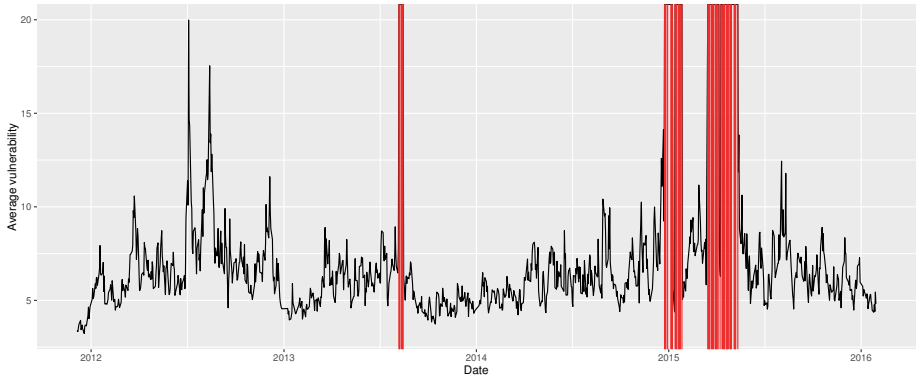
$$Av. vulenr. = \frac{sum(C^B(1))}{n}$$

Weighted vulnerability is Bonacich centralities weighted by market capitalization of each firms

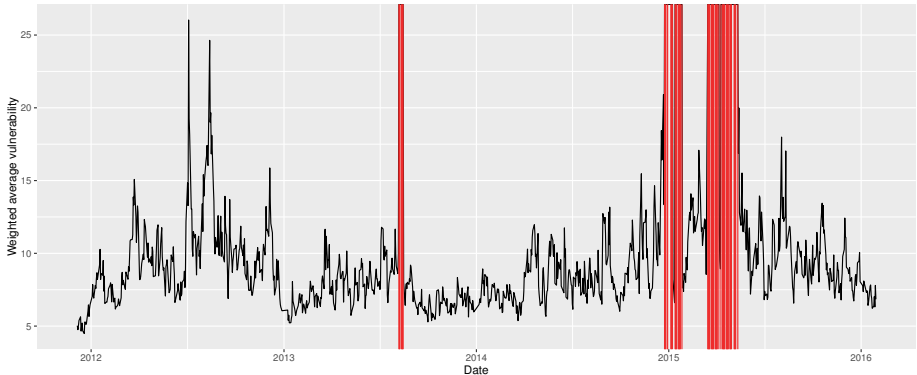
Maximum absolute eigenvalue



Average vulnerability



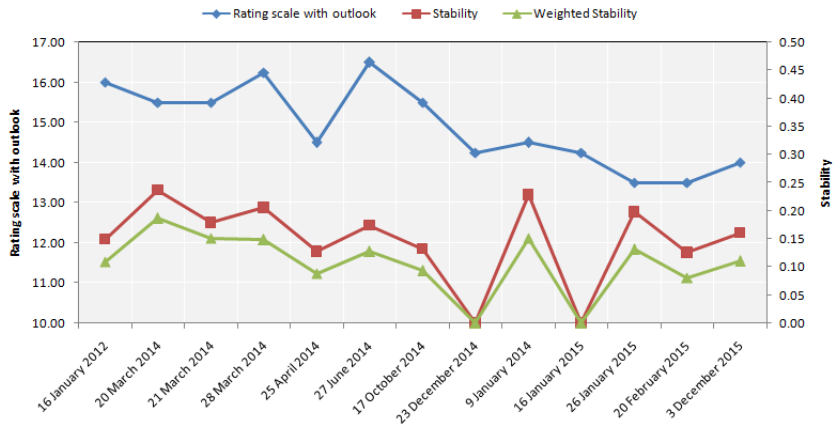
Weighted average vulnerability



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 |

Credit rating and vulnerability measures



Conclusion

Conclusions

- We mapped most liquid and major firms in Russian Stock Market
- We proposed to distinguish degree centrality for network with positive and negative connections
- Most connected firms: Sberbank and Lukoil. Most central in terms of systemic risk: Gazprom and FGC UES.
- The key network measures were examined over time
- Interconnectedness strengthen during the crisis
- We calculate vulnerability of the system to systemic risk

Partial Correlation

- Partial correlation, $\rho_{i,j|}$, between X_i and X_j shows linear dependence between them excluding influence of the rest of components of X
- Recall,

$$R = D_{\Omega}^{-1/2} \Omega D_{\Omega}^{-1/2} \quad r_{i,j} = \frac{\sigma_{i,j}}{\sqrt{\sigma_{i,i}, \sigma_{j,j}}}$$

$$D_{\Omega} = \text{diag}\{\sigma_1^2, \dots, \sigma_n^2\}, \quad \Omega = \text{cov}(X)$$

- Similarly,

$$P = D_K^{-1/2} K D_K^{-1/2} \quad \rho_{i,j|} = \frac{k_{i,j}}{\sqrt{k_{i,i}, k_{j,j}}}$$

where $K = \Omega^{-1}$ or $K = R^{-1}$

back