

Approaches to identification of substandard transactions on Russian financial market

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PROGNOZ
RISK LAB

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How to reveal the market misconduct

- By whistleblowers practice
(FSA Whistleblower line (UK, 2002); SEC Whistleblower Program (US, 2011) etc)
- Revealing statistical patterns for case studies
(Jiang et al (2004) , Misra et al (2011))
- By “blanket” filters covered the whole market
 - Analyzing unexplainable “abnormal” returns (Mitchell, Netter (1994))
 - Building statistical bands for non-misconducted dynamics and tracing the exceptions (Minenna (2003), Cholewinski (2009))

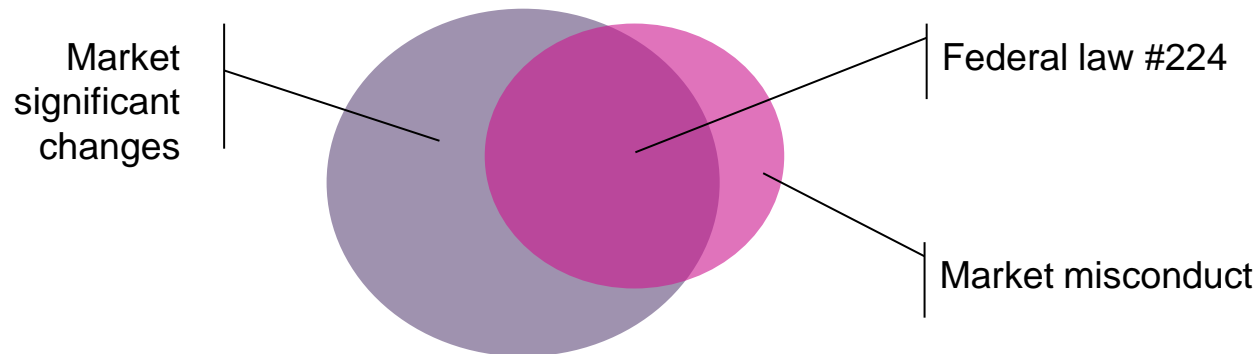
Approaches and metrics

Russian regulating acts:

Federal law #224 (came into operation on 27-jan-2011)

supported with the methodic documents on identification the “significant deviation” of transactions:

- № 11-21/пз-н and 1-38/пз-н (deals prices)
- № 11-70/пз-н (deals volume)
- №11-71/пз-н (demand and supply)



Project summary

Research aims:

To calibrate the models of market misconduct algorithmic identification;
The main challenge is to make academic mathematical models consistent with the federal law requirements.

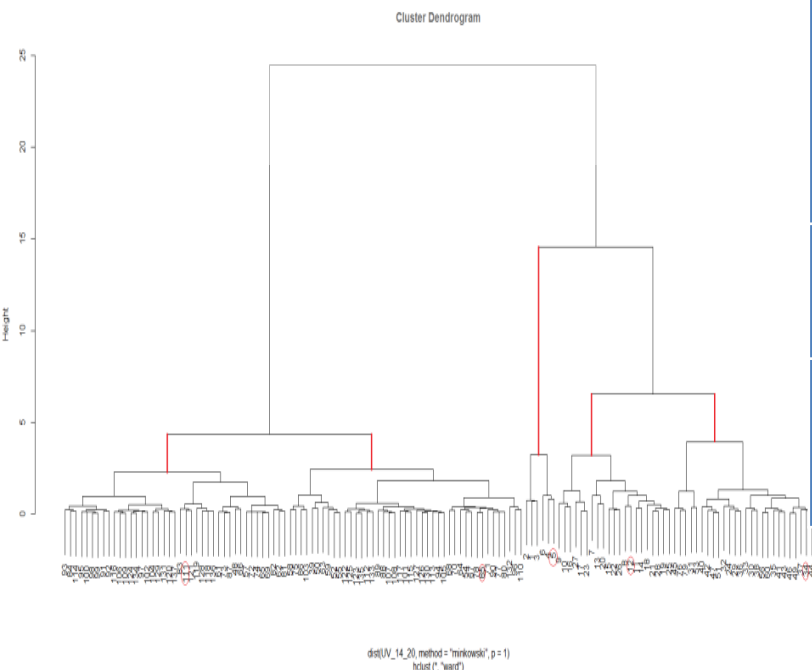
Research was done in the interest of FFMS (Russia)

Raw data

- Equity sector of MICEX-RTS
- Sample for 01-sep-2011 – 30-nov-2011
- Agent-resolved executions and orders

Securities sampling

- ❑ Securities population was divided by types and liquidity
- ❑ Number of k liquidity homogeneous groups was defined through divisive hierarchical clustering
- ❑ The final sample consists of k -means clusters centers for each security group



Security sample	Ticker (MICEX)	Average trade volume, thousand roubles	Average number of trades per day	Number of unique market participants	Average number of unique market participants per day
Low liquid stocks	YKENP	304,3	15	170	50
	TGKJ	319	27	337	58
	SVTZ	14	2	51	26
	MOTZ	190,5	11	168	43
Liquid stocks	MTLR	132 125,8	3 286	10 728	1 067
	GAZP	12 977 861	84 430	68 886	9 962
	KOGK	2 853,9	19	284	43
	NLMK	582 010,1	11 864	21 967	2 801
	PKBA	1 007,7	50	465	86
	VTBR	2 552,6	33 734	37 384	4 652
	SYNG	2 266,3	107	901	102
	AVAZ	4 007,3	283	2 149	240
Low liquid bonds	RU000A0JR6Z3	6 823,6	3	76	11
	RU000A0JRFH3	2 988,4	1	42	4
	RU000A0JR0D3	10 154,2	1	72	6
	RU000A0JPWJ8	984,1	2	41	11
Liquid bonds	RU000A0JQLW2	12 395,5	15	355	32
	RU000A0JR8R6	3 966,4	11	241	29
	RU000A0JR2Z2	1 883,7	10	164	31
	RU000A0JQY92	4 762,4	4	59	9
	RU000A0JQTB9	26 305,5	2	82	13

Price significant deviation

The applied approaches:

Parametric thresholds based on market dynamics

$$T = Z \cdot \sigma + k(\beta) + R$$

$$T = Z \cdot C \cdot \sigma + k(\beta) + R$$

*the σ -s are different depending on the number of market participants

(the alternative is expert thresholds settings – hierarchical filters system:

$$\{T_1 = const \dots T_i = f(P) \dots T_n = \dots \}$$

Price variation thresholds

The σ –s distributions and variations differ significantly

Security sample	Securities	Average deals price variation		Close-to-close volatility		Average close-to-close volatility to average deals prices deviation	Threshold 3 σ to average deals prices deviations
		Mean	Std.dev	Mean	Std.dev		
Low liquid stocks	YKENP	1.59%	1.38%	3.86%	0.69%	2.124	6.373
	TGKJ	0.86%	0.82%	2.40%	0.37%		
	SVTZ	3.57%	4.28%	3.82%	0.46%		
	MOTZ	1.26%	1.29%	2.79%	0.45%		
Liquid stocks	MTLR	1.49%	1.13%	4.05%	0.61%	3.030	9.090
	GAZP	0.91%	0.59%	2.57%	0.20%		
	KOGK	1.23%	1.20%	3.22%	0.48%		
	NLMK	1.45%	1.26%	4.34%	0.64%		
	PKBA	0.63%	0.80%	1.58%	0.43%		
	VTBR	1.06%	0.92%	2.93%	0.29%		
	SYNG	0.85%	0.87%	3.88%	0.40%		
	AVAZ	0.83%	0.80%	2.68%	0.22%		
Low liquid bonds	RU000A0JR6Z3	0.46%	0.83%	1.07%	0.34%	3.375	10.125
	RU000A0JRFH3	0.04%	0.16%	0.26%	0.03%		
	RU000A0JR0D3	0.07%	0.11%	0.21%	0.03%		
	RU000A0JPWJ8	0.57%	0.98%	0.88%	0.17%		
Liquid bonds	RU000A0JQLW2	0.17%	0.42%	0.34%	0.12%	2.947	8.841
	RU000A0JR8R6	0.15%	0.19%	0.48%	0.11%		
	RU000A0JR2Z2	0.30%	0.31%	1.12%	0.21%		
	RU000A0JQY92	0.33%	0.53%	1.10%	0.38%		
	RU000A0JQTB9	0.11%	0.33%	0.27%	0.07%		

Crisis adjustment

	Russian blue chips (MICEX30)		US blue chips (DJIA)	
Observation period	Crisis	Non-crisis	Crisis	Non-crisis
Average daily volatility (close to close)	4.85%	2.26%	3.67%	1.41%
Average intraday volatility (close to open)	5.2%	2.23%	3.02%	1.04%

$$T_1 = Z \cdot \sigma$$

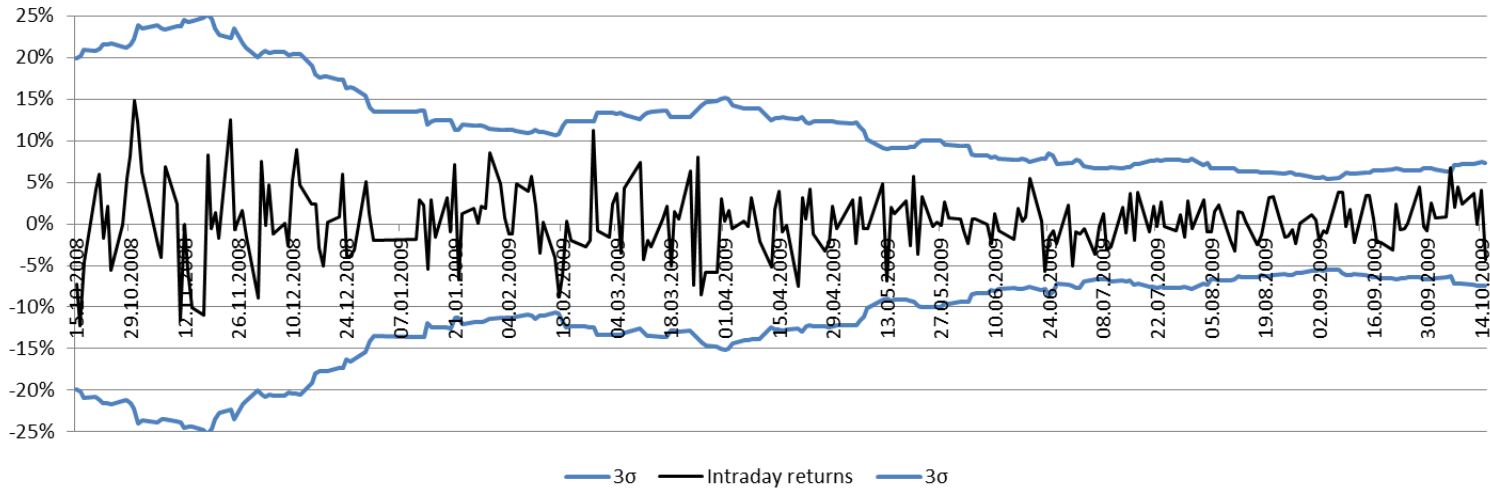
$$T_2 = Z \cdot \sigma + f(\beta)$$

	Russian blue chips (MICEX30)		US blue chips (DJIA)	
Observation period	Crisis	Non-crisis	Crisis	Non-crisis
Sample size	7 500	7 573	7 432	7 710
Exceptions (T_1)	1.41%	1.58%	0.71%	0.99%
Exceptions (T_1^*)	1.63%	1.65%	0.31%	0.29%
Exceptions (T_2)	1.36%	1.43%	0.51%	0.71%
Exceptions (T_2^*)	1.59%	1.53%	0.22%	0.25%

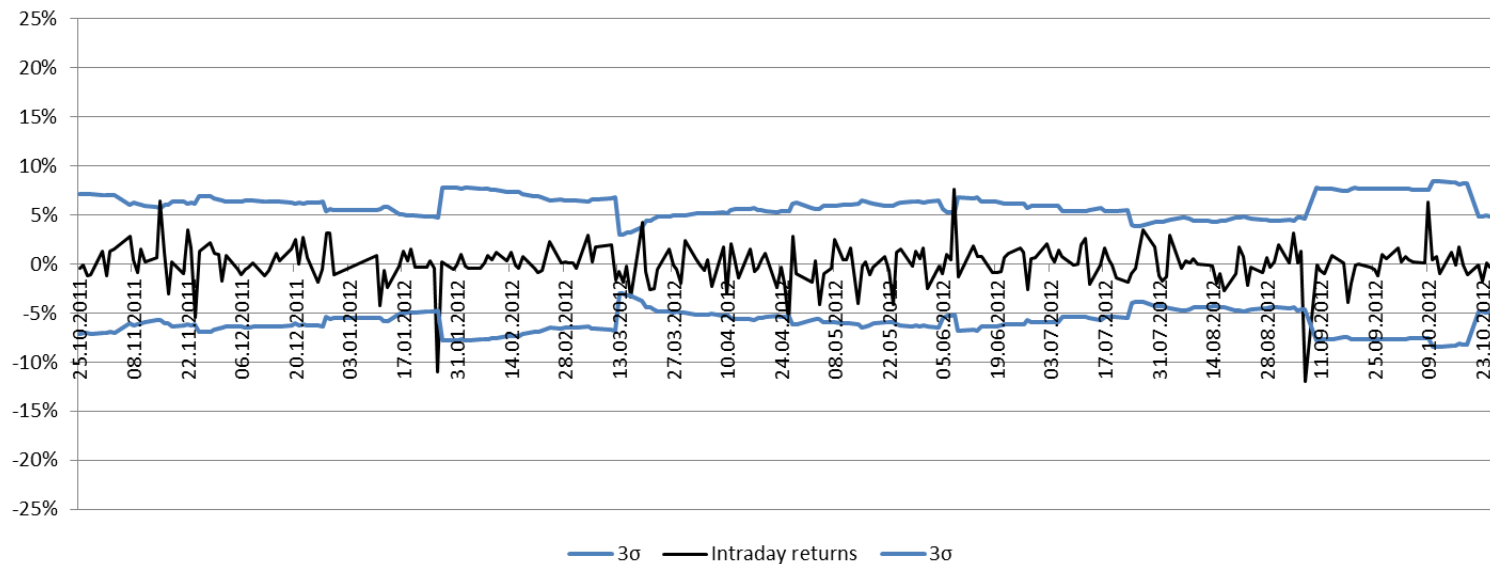
* indicates thresholds with intraday volatility

Crisis adjustment

"Gazpromneft" (SIBN), 15.10.2008 - 15.10.2009



"Gazpromneft" (SIBN), 25.10.2011 - 25.10.2012



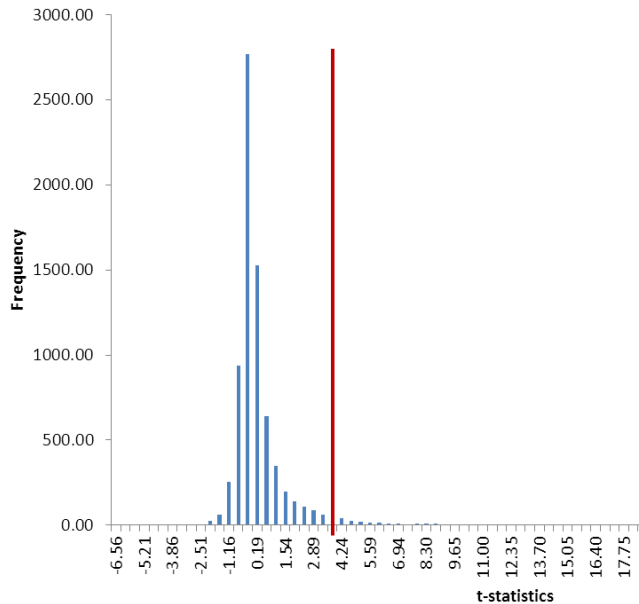
Volume significant deviation

The applied approaches:

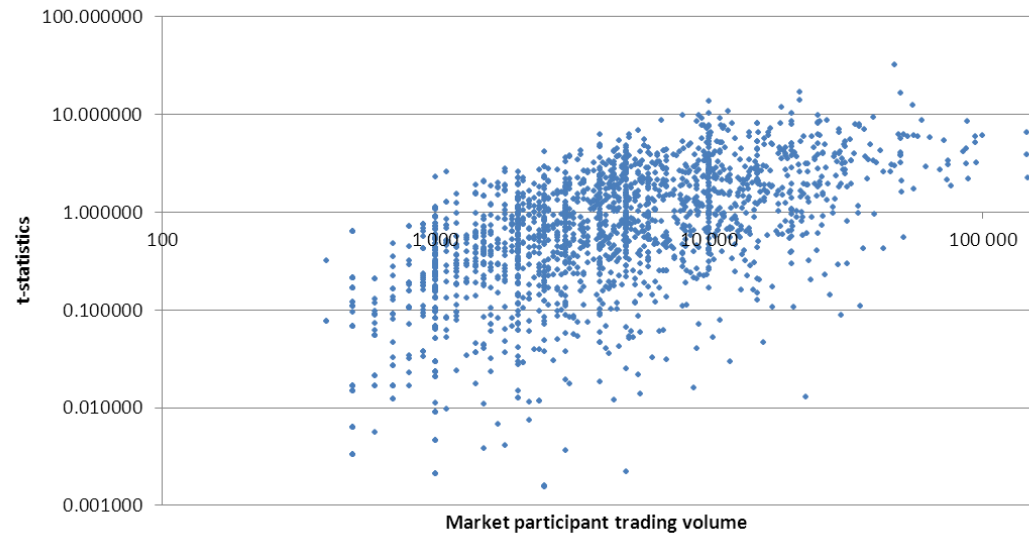
Regression methods to identify the most significant market participants

$$Y = \alpha + \theta \cdot Dummy^p + \epsilon$$

t-statistics histogram



t-statistics vs trading volume (AVAZ) (log-log scale)



Open questions and perspectives

- Theoretical issues

how to distinguish between trading strategy aimed at profit (*even if it harms the market quality!*) and purposeful market manipulation

- Manipulation horizons

Schemes intuitively seem to be dependent on manipulation time scale (intraday, end-of-day, multiple days...)

- Systemic risks, including high frequency traders (HFT) impact

how robust is the market as a whole system?

what happens due to collective dynamics of multiple algorithms driven market participants?

- ...

Questions?

Thank you
for your attention

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