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Performance of American and Russian Joint Stock Companies on Financial Market. A Microstructure Perspective

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Abstract: *This paper compares the periods before and after the Ukrainian crisis of 2014 from the perspective of market microstructure. The hypothesis is that the crisis influenced the fragile Russian financial market equilibrium. As financial markets adapt to the new equilibrium, the paper studies the effects of the crisis and the imposition of economic sanctions on Russia in terms of volatility, duration, prices and volume for selected joint stock companies listed on the U.S. and the Russian stock markets. Results reveal that the Moscow Stock exchange lacks an appropriate transmission mechanism from informed investors to the rest of the market.*

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Introduction

Financial market microstructure has been a subject of many theoretical and empirical analyses. It is supported by the development of information systems that utilizes big-data bases and designs tools for its analysis. Such technological advances are accompanied by development of models and analytical methods for ultra-high frequency data. It is considered as the most important achievements of financial econometrics and contemporary finance (Engle, 2000).

Microstructure models offer an appropriate method for comparing the dynamics of different financial instruments since they make a precise inference about short term market sensitivity. Investors usually act based on contemporaneous and historical information combined with their own opinions. Microstructure models are comparable to heterogeneous investors within three types, i.e., informed investors, noise investors and market-makers. The main feature that distinguishes these three groups is their access to information.

Many theoretical models concerning an ideal market that reflects all possibly available information have been constructed (see, for example, Russell & Engle, 2010). One observes two things when examining the models starting with Bagehot (1971), Garman (1976), and Grossman and Stiglitz (1980), through more complicated models formulated by Kyle (1985) or Admati and Pfleiderer (1988) and a recent models developed by Hasbrouck (2002). First, is the division of financial markets models into a price-driven and an order-driven market models. The second is the evolutionary complication of the models. All these mentioned models as well as many others are discussed in details by Doman (2011).

The most important issues that create market microstructure are access to information possessed by market participants. That is why three types of investors are typically defined: the informed investors, the market makers and the noise traders (Doman, 2011). While observing thick-by- thick time series data, one can detect the changes in the structure of the market during a certain time period and evaluate the quality of the market. The market quality is defined in terms of liquidity. Liquidity refers to the ability to quickly trade high volumes at low cost. Other possible attributes of liquidity can be considered, such as the frequency with which an asset is traded, the resiliency of a market which makes trades less able to execute at inappropriate prices, transaction costs, sensitivity of prices to information and price volatility. The last issue has a significant impact on market values.

The empirical analyses of financial markets microstructure has become popular starting from the seminal book by O'Hara (1995). They are currently of a great importance due to the emerging markets development, foreign exchange market analysis and market stability policy after the financial crisis of 2007–2009. For example, Yuan *et al.* (2015) analyze shares of real estate companies traded in Shanghai stock exchange focusing on liquidity. They implement various forms of Weibull Autoregressive Conditional Duration (WACD) models using trading duration as indicators for liquidity.

Bień (2010) studies the market microstructure of the forex (FX) euro/Polish zloty (EUR/PLN) spot market. She shows a significant positive impact of order flow on changes in the exchange rate, as well as a different FX rate reaction to the net acquisition of euros in 2004 and in 2007, due to the different size of the Polish zloty market. As in the case of emerging markets, the problem of liquidity affected the results of the study. Frank (2009) analyzes market co-movements during the global financial crisis. Using high frequency data, he accounts for market microstructure noise and non-synchronous trading, as well as interdependencies between differing asset classes such as equity, FX, fixed income, commodity and energy securities. He applies multivariate realized kernels and Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) models.

The results of the microstructure analysis show that they are difficult to be generalized since they depend on the time-periods chosen for an investigation. The publication of Admati and Pfeiderer (1988) demonstrates important theoretical indications for regularities observed in financial markets. Although some similarities can be observed, they may not be present in a particular circumstance (Bień, 2010). For example, Admati and Pfleiderer (1988) show that in periods of large volume of transaction, investors are guided by signals extracted from the information flows. This rule may not always be valid. That is why microstructure studies are subject to various, competing interpretations.

This paper uses data from the mature American and the Russian emerging stock markets. The purpose is to compare two different periods – before and after the Ukrainian political crisis at the beginning of 2014 from the perspective of market microstructure. This crisis influences the fragile, emerging Russian financial market equilibrium. The crisis can be viewed as a permanent structural break. As markets adapt to the new equilibrium, the paper studies the effects of the Ukrainian crisis and the imposition of economic sanctions on Russia. The Russian and Ukrainian financial markets are rarely a subject of profound research. However, one finds some recent publications. For example, Caporale and Plastun (2016) investigate calendar effects for the Ukrainian stock market using daily and monthly data. Microstructure-effects of the Russian currency market are analyzed by Obizhaeva (2016). Osinska (2010) uses realized volatility to evaluate the quality of volatility forecasts for several emerging currencies including the Russian ruble.

The paper investigates the relationships between volatility, duration, price and volume for selected joint stock companies listed on the United States (U.S.) and the Russian stock markets. These markets are the New York Stock Exchange (NYSE), the National Association of Securities Dealers Automated Quotations System (NASDAQ) and the Moscow Stock Exchange (MOEX). Furthermore, the study compares the microstructure effects of the first phase of the Ukrainian crisis (from February 17, 2014 until April 4, 2014) and a more neutral period of the same length (from September 1, 2013 until October 17, 2013).

The paper utilizes a variety of econometric time series models. Specifically, the following models are estimated: The Exponential Generalized Auto-Regressive Conditional Heteroskedasticity, EGARCH(p,q) model (see: Bollerslev & Mikkelsen, 1996). Next, the Autoregressive Conditional Duration (ACD) is introduced (Engle & Russell, 1997). The ACD model is followed by the Autoregressive Conditional Volume (ACV) model for volume. The last econometric model is the one developed by Manganelli (2005) which uses Vector Autoregressive Moving Average (VARMA) specification. The Manganelli (2005) model is a generalization of both the ACD and the ACV models. Doman and Doman (2010) use the above procedure to analyze relationships between price duration, volatility, volume and return for the Warsaw Stock Exchange. This paper is the first to apply these econometrics methods to Russian and American stocks before and after the Ukrainian crisis.

Theoretical models that explained microstructure effects on financial markets are used for explanation and interpretation of the results. The most helpful in our research is the model formulated by Admati and Pfleiderer (1988).

The remainder of the paper is organized as follows: Section II describes the characteristics of the stock exchanges, the New York Stock exchange (NYSE), the National Association of Securities Dealers Automated Quotations System (NASDAQ) and the Moscow Stock Exchange (MOEX). Section III presents the econometrics models. These models are presented in the following order: The Exponential Generalized Autoregressive Conditional Heteroskedasticity, EGARCH(p,q) Model, the Autoregressive Conditional Duration (ACD) Model, the ACV model for volume and the Manganelli model. Section IV describes the data. Section V presents and discusses the results of the econometric estimation. Section VI concludes.

Characteristics of the Stock Markets

This section presents the characteristics of the stock markets under investigation. These are: the New York Stock Exchange (NYSE), the National Association of Securities Dealers Automated Quotations System (NASDAQ) and the Moscow Stock Exchange (MOEX). Table 1 provides data about the starting year of the stock exchange, its market capitalization as of March 2014, the number of stocks traded, market capitalization per share and trading hours per day. The New York Stock Exchange is the oldest market among the three, being established in 1792. It is the largest stock exchange in the world in terms of market capitalization. In contrast, the Moscow Stock Exchange is the youngest among the three, being initiated in 2011.

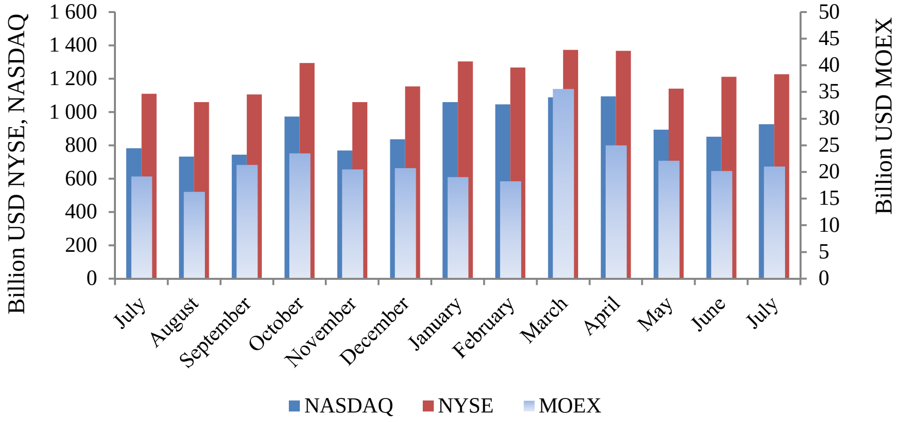
Table 1. Characteristics of the stock markets

	NYSE	**NASDAQ**	**MOEX**
Starting year	1792	1971	2011 (MICEX 1992) (RTS 1995)
Capitalization*	18.5 trillion USD	6.5 trillion USD	663 billion USD
No of stocks	2400	2740	270
Capitalization per share	7.6	2.45	2.44
Trading hours a day	6.5	6.5	8.5

*As of March 2014

Source: own preparation based on http://moex.com/en; http://www.nasdaq.com; https://www.nyse.com.

Figure 1. Trading volume from July 2014 until July 2015



Source: own preparation based on http://moex.com/en; http://www.nasdaq.com; https://www.nyse.com.

Figure 1 depicts the trading volume from July 2014 until July 2015. Except for the month of March 2015, the trading volume is ordered as NYSE, NASDAQ and MOEX.

Figure 1 shows that thee markets are different from each other. However, one expects that the characteristics of the market microstructure are replicated for the markets under study.

The Eeconometric Models of Market Microstructure

Models that focus on microstructure effects rely on the general concept of financial market equilibrium developed by Kyle (1985), Admati and Pfleiderer (1988) and it is still in the developing process (see, for example, Kyle & Obizhaeva, 2016). In financial markets, equilibrium means market liquidity that is understood as a possibility of transactions using different information sets for various investment horizons.

This paper applies several econometric models that focus on microstructure effects, i.e., the impact of receiving new information on liquidity of both separate instruments and the market as a whole. After preparing the data by elimination of deterministic components that characterizes thick-by-thick data like periodicity, one can analyze the following elements: intraday volatility, intraday price duration and intraday volume duration. They can be described separately or jointly in one model. The presented models start from sequent components model and finally connect all the elements into one model. Exponential GARCH model EGARCH(p,q) used for both volatility and asymmetry analysis is the first specification (for details see: Nelson, 1991; Bollerslev and Mikkelsen, 1996). The model proposed by Bollerslev and Mikkelsen takes the following form:

$$\ln \sigma_t^2 = \omega + [1 - \beta(L)]^{-1} [1 + \alpha(L)] \gamma(\varepsilon_{t-1}) \tag{1}$$

where: $\alpha(L) = \alpha_1 L + \alpha_2 L^2 + \dots + \alpha_q L^q$; $\beta(L) = \beta_1 L + \beta_2 L^2 + \dots + \beta_p L^p$ and $\gamma(\varepsilon_{t-1}) = \gamma_1 \varepsilon_{t-1} + \gamma_2 (|\varepsilon_{t-1}| - E|\varepsilon_{t-1}|)$. The difference between $|\varepsilon_{t-j}|$ and its expected value influences the change of the conditional variance depending on the direction and magnitude of the difference, whereas the expected value $E|\varepsilon_t|$ depends only on the error ε_t distribution. The model specifications allow for negative correlation between return and volatility and simulating variance clustering. It can model the variance explosion that occurs fairly frequently. In the paper a skewed t-Student error distribution was assumed to cover a possible asymmetry and leptokurtosis. It is a general volatility model that suits not only thick-by-thick data but also daily data and other frequencies. It is worth noting that non-negativity of conditional variance is ensured by the construction of EGARCH model.

The second model that appeared in our analysis is the Autoregressive Conditional Duration model (ACD) introduced by Engle and Russell (1997). The idea of the price duration corresponds to market liquidity. The rule is as follows: the shorter the duration - the most liquid is the market. Thus, the model traces the dynamics of the market during a trading day. The first specification of the model proposed by Engle and Russell was extended in such a way that a family of ACD models can be considered (Fernandes and Grammig, 2006; Zhang, Russell and Tsay, 2001). Let the time between sequent transactions in the market be $d_i=t_i-t_{i-1}$ where d_i represents a duration. Let ψ_i be an expected conditional price duration given information available at moment i-1 $E(d_i|F_{t-i})= \psi_i$. Specifically, $\psi_i=E(d_i|d_{t-1},d_{t-2},\ldots,d_1)$. Duration $d_i= \psi_i\xi_i$, where ξ_i is i.i.d. and $E(\xi_i)=1$. Generally, exponential and Weibull distributions fit well distribution of ξ_i. The ACD model for price duration is as follows

$$\psi_t = \omega + \sum_{j=1}^{q} \alpha_j \; d_{t-j} + \sum_{j=1}^{p} \beta_j \psi_{t-j} \tag{2}$$

where $\omega>0$, $\alpha_j\geq0$, $\beta_j \geq0$ for each j. The model can be estimated using quasi-maximum likelihood method (Allen, Ng and Peiris, 2013).

The third model is the autoregressive conditional volume (ACV) (see, Manganelli 2005). It covers the dynamics of volume and it is defined as follows. Let w_i be a volume, and v_i conditional expected volume given information up to moment i-1. Then $w_i = v_i\eta_i$. where η_i is i.i.d. and $E(\eta_i)=1$. The ACV model takes the following form:

$$v_i = \omega + \sum_{j=1}^{q} \alpha_j \; w_{i-j} + \sum_{j=1}^{p} \beta_j v_{i-j}, \tag{3}$$

where $\omega>0$, $\alpha_j\geq0$, $\beta_j \geq0$ for each j. The ACD and ACV models can be thought as complementary because the change in price or volume is being interpreted as the result of the intensity of new information arriving to the market. In ACV model, the same error distributions as in ACD model can be applied. Mainly it is a Weibull distribution. Other characteristics of the model are also analogous to ACD.

The last model is the one proposed by Manganelli (2005). It is called Manganelli model. It represents a linear relationship between price duration, volume and volatility of the general form such that:

$$(d_t, w_t, r_t) \sim f(d_t, w_t, r_t | F_{t-1}; \Theta) =$$
$$= \mathrm{g}(d_t | F_{t-1}; \Theta_1) \mathrm{h}(w_t | d_t, F_{t-1}; \Theta_2)\, \mathrm{l}(r_t | d_t, w_t, F_{t-1}; \Theta_3) \tag{4}$$

where: $d_t = \psi_t(\Theta_d; F_{t-1})\xi_t, \quad \xi_t \sim iid(1, \sigma_\xi^2)$;
$w_t = v_t(\Theta_w; d_t; F_{t-1})\eta_t, \quad \eta_t \sim iid\left(1, \sigma_\eta^2\right)$
$r_t = \mu_t + \sigma_t(\Theta_r; d_t; w_t; F_{t-1})\varepsilon_t, \quad \varepsilon_t \sim iid(1, \sigma_\varepsilon^2)$. In practice, separate equations or VAR or VARMA models are used.

Characteristics of Time Series

Three types of companies chosen are based on the greatest liquidity of the companies' shares on both the Russian and American stock markets. For that reason, the size and familiarity of the companies are examined. Companies' shares under investigation include: shares quoted on MOEX market in Moscow such as: Aeroflot (ALFT), Rosneft (ROSN) and Rostelecom (RTKM); Russian shares in the U.S. market represented by: Yandex (YNDX) and CTC Media (CTCM) and American companies' shares traded on the NASDAQ market i.e., Microsoft (MSF) and Yahoo (YAHOO) and on the NYSE i.e., Exxon Mobil (XOM) and Mc Donald (MCD).

The time series include thick-by-thick data covering two separate periods – the same for each company quotations. The first period is from 2013-09-02 until 2013-10-17 and the second period from 2014-02-17 until 2014-04-04. The first period covers a relatively stable time period from economic and financial perspective, while the second one is determined by the annexation of Crimea, which has started the Ukrainian crisis. These caused imposing international economic sanctions on Russia. The first round of sanctions took place in March/April 2014 and the second in April 2014. These facts might have changed the riskiness of investment in Russian companies. Thus, we analyze and compare the microstructure of the three mentioned markets: emerging market represented by Russian MOEX, and matures markets, represented by the American NASDAQ and NYSE. Additionally, we investigate whether there is any difference between the microstructure effects of emerging and developed markets.

When one analyzes thick–by-thick data, the problem of ultra-high frequency data arises (see: Engle & Russell, 2004; Scalas *et al.*, 2004; Sewell *et al.*, 2008). The main problems that are faced by analysts are the following: an overnight duration, transactions registered at the same moment in time and intraday cyclical patterns. Consequently, the data must be adjusted before the analysis starts. This paper applies the procedure described by Doman (2010). The characteristics of the data are presented in Table 2.

Table 2. Reduction of the number of observations and dynamics of the number of transactions

Period	**2013-09-02 - 2013-10-17**		**2014-02-17 - 2014-04-04**		**% change of number of transac-tions**	**% change of average volume of transactions**
Type of the data	**Trading day**	**Corresponding to price duration**	**Trading day**	**Corresponding to price duration**		
AFLT	69 269	20 135	278 907	80 707	302.64	7.95
ROSN	396 412	65 031	681 421	83 618	71.96	N.A.
RTKM	274 595	62 116	424 523	63 005	54.71	N.A.
CTCM	13 086	4 276	33 151	4 489	153.33	11.38
YNDX	44 993	17 559	115 807	46 355	157.39	65.46
MCD	107 564	36 315	101 006	39 693	-6.10	-1.64
MSFT	863 418	65 314	648 126	58 452	-24.93	-45.32
YA-HOO	302 102	52 425	318 682	60 154	5,49	N.A.
XOM	239 790	53 432	246 920	69 812	2.97	-24.12

Source: own calulations.

It is worthwhile to note the differences between these shares. First, there is a substantial difference between the number of transactions for a whole trading day and the price duration. This is due to huge liquidity of the analyzed shares where many transactions are observed at the same time period. Thus, for further econometric analysis, we use the observations that correspond to price duration. Second, note that for the Russian stock market, the number of orders in the year 2014 increased more than three times when compared with 2013 including, an increase of the average value of the transactions. Third, for two shares, namely the CTCM and YNDX listed on the American markets, a similar tendency concerning growth of the average value of the transaction are observed. For American companies' shares, the situation was quite different. The trade was quite stable for he two periods, in term of both the dynamics and the value of transactions.

Table 3. AFLT - descriptive statistics for price, return, absolute return volume and duration in 2013 and 2014

Variable	Price		Return		Absolute return		Volume		Duration	
Statistics	**2013**	**2014**	**2013**	**2014**	**2013**	**2014**	**2013**	**2014**	**2013**	**2014**
Mean	49.46	57.80	0.000010	-0.000004	0.0007595	0.0007231	3 584	3 869	53.6	13.4
Median	49.40	55.70	0.000034	-0.000015	0.0004854	0.0004970	800	1 300	20.0	5.0
Minimum	46.44	44.77	-0.007857	-0.080698	0.0000011	0.0000002	100	100	1.0	1.0
Maximum	51.75	82.14	0.009071	0.033126	0.0090717	0.080698	207 100	771 100	2 052.0	2 560.1
St. Dev.	1.53	8.50	0.001106	0.001189	0.0008050	0.000943	9 933	10 449	98.6	32.4
Variability	0.03	0.15	102.65	264.04	1.06	1.31	2.77	2.70	1.8	2.4
Skewness	-0.24	1.10	0.17	-4.03	2.77	13.79	8.24	16.94	6.0	14.3
Kurtosis	-1.19	0.67	6.32	314.27	13.73	750.06	105.09	678.46	65.5	621.0

Source: own calculations based on the data retrieved from http://www.aeroflot.ru/cms/en.

Table 4. XOM - descriptive statistics for price, return, absolute return volume and duration in 2013 and 2014

Variable	Price		Return		Absolute return		Volume		Duration	
Statistics	**2013**	**2014**	**2013**	**2014**	**2013**	**2014**	**2013**	**2014**	**2013**	**2014**
Mean	87.80	95.46	0.0000005	0.0000005	0.000121	0.0001400	549.76	417.11	15.1	11.3
Median	87.75	95.07	-0.000008	-0.000008	0.000113	0.0001056	300.00	300.00	8.0	6.0
Minimum	86.81	93.07	-0.002455	-0.013480	0.000000	0.0000002	100.00	100.00	1.0	0.5
Maximum	88.88	98.83	0.003290	0.011351	0.003290	0.0134800	17 220.00	25 327.00	557.7	1238.7
St. Dev.	0.51	1.45	0.000160	0.000204	0.000104	0.0001488	642.80	525.23	21.2	16.1
Variability	0.01	0.02	301.20	427.53	0.85	1.06	1.17	1.26	1.4	1.4
Skewness	0.21	0.56	1.41	1.61	8.12	27.69	4.82	7.72	5.2	12.7
Kurtosis	-0.72	-0.83	34.23	534.96	158.00	1 799.90	56.91	155.66	62.1	652.0

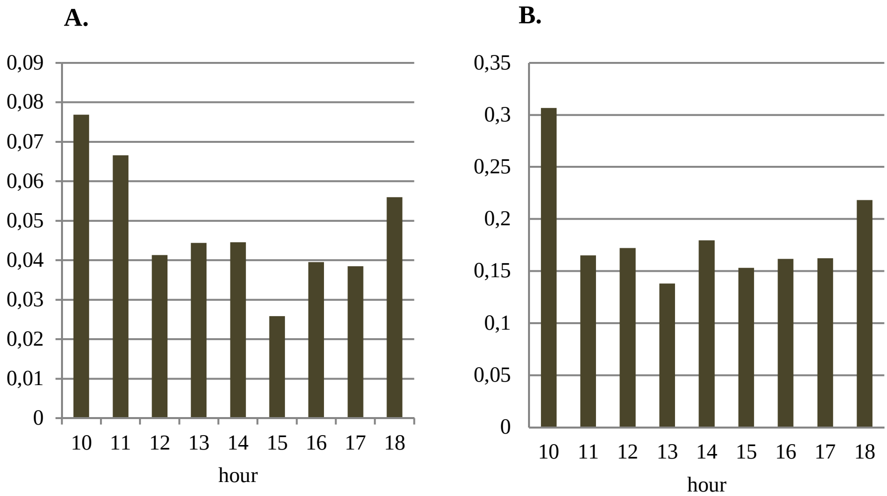
Source: own calculations based on the data retrieved from http://corporate.exxonmobil.com.

To save space, Tables 3 and 4 detail information about two companies' shares.[1] These are descriptive statistics for price, return, absolute return, volume and duration in 2013 and 2014 for Aeroflot (ALFT) and Exxon Mobil (XOM).

The next stage of analysis concerns the analysis of the cyclical patterns. It is typical that at the beginning of the Russian trading day, the increased price levels and volumes and shorter price durations are related with the investors' interest confirmed by flows of information coming from both Asian markets that end their trading day and the European markets beginning their trading day. Then, a slow-down happens which is caused by investors' reactions to news stems from the American markets. The results for ALFT and XOM are presented in figures 2 and 3. The remained Russian and American shares represent a similar cyclical pattern.

Figure 2. ALFT - cyclical patterns in absolute returns, duration and volume

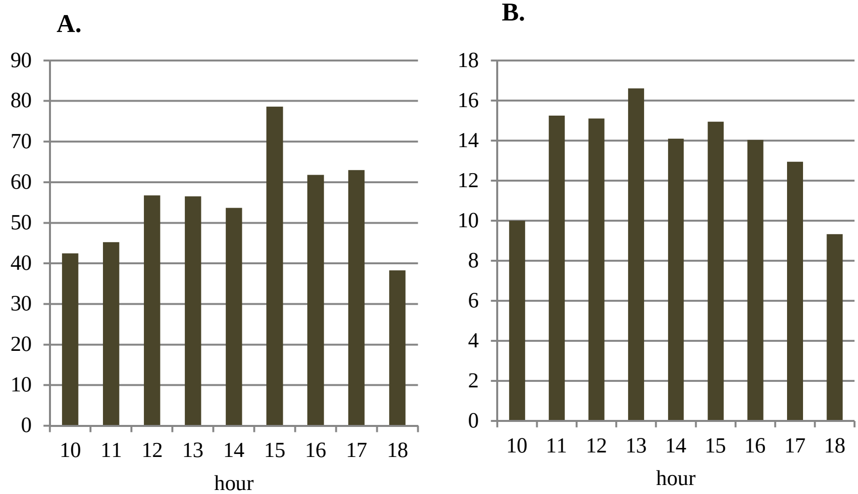
Intraday average absolute returns from 01.09.2013 to 17.10.2013 (A) 17.02.2014 to 04.04.2014 (B)



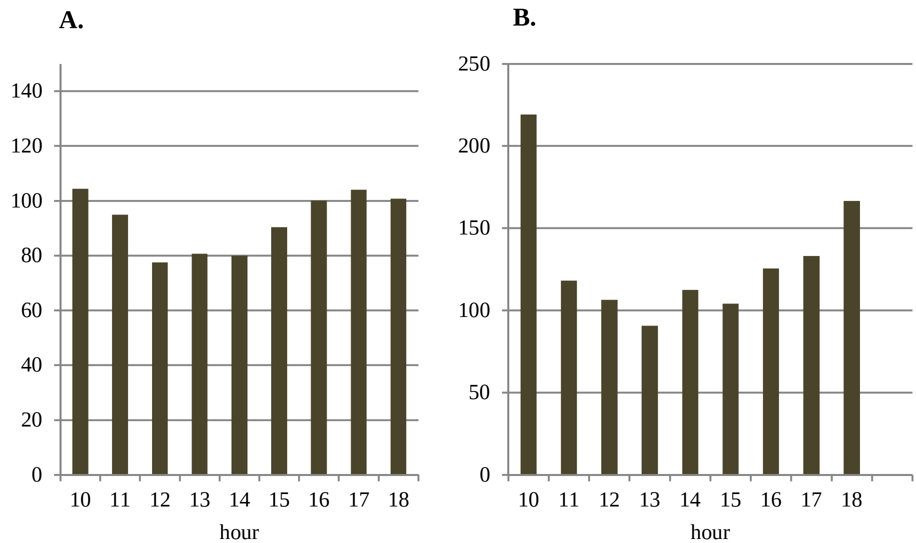
[1] Ccharacteristics computed for the remained companies' shares are available from the authors for request.

Figure 2 continued

Intraday average duration from 01.09.2013 to 17.10.2013 (A) and from 17.02.2014 to 04.04.2014 (B)



Intraday average volume from 01.09.2013 to 17.10.2013 (A) and from 17.02.2014 to 04.04.2014 (B)



Source: own calculations.

For ALFT shares, one notices differences in the daily distribution of absolute returns. For the first period (left-hand-side in Figure 2), the typical U shape is observed, which means that greater changes in prices are observed in the first and the last hour of the trading day. In the year 2014, the same tendency remained, however, an increase in absolute returns is observed in the middle of the trading day. Average durations are an inverse U- shaped. In comparison to the typical tendency (observed for example for XOM, see Figure 3), this shape is flatted and skewed. As far as volume is concerned, increased values are confirmed in the first and the last hour of the trading day in 2013. For the year 2014, an increase in trading volume for particular hours is observed.

Figure 3. XOM - cyclical patterns in absolute returns, duration and volume

Intraday average absolute returns from 01.09.2013 to 17.10.2013 (A) 17.02.2014 to 04.04.2014 (B)

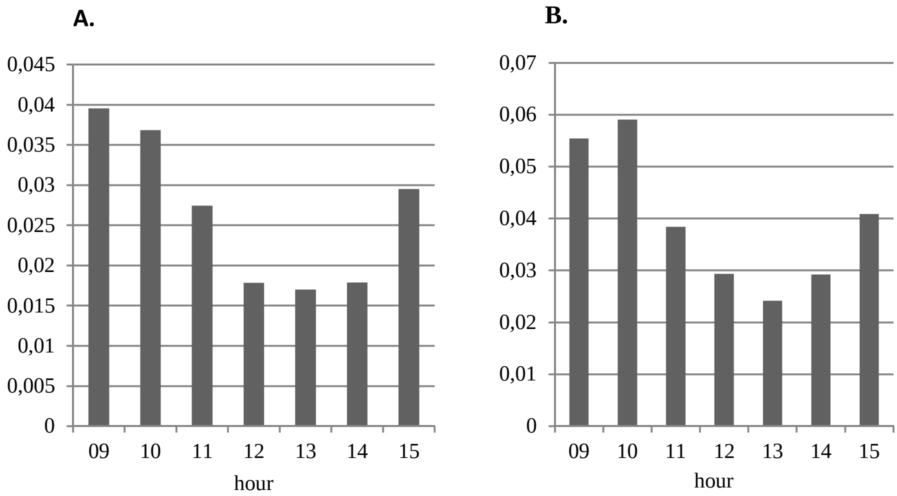
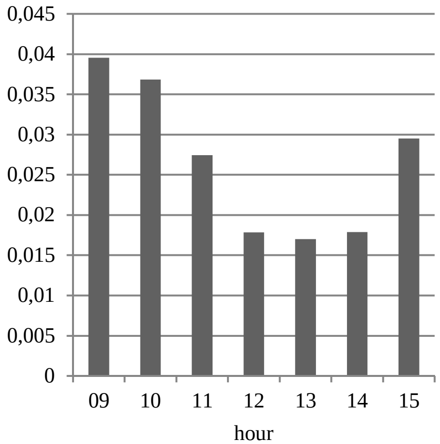


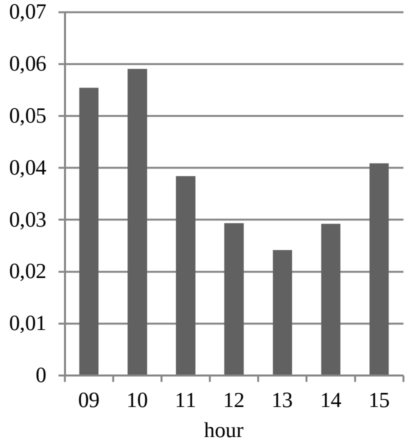
Figure 3 continued

Intraday average absolute returns from 01.09.2013 to 17.10.2013 (A) 17.02.2014 to 04.04.2014 (B)

A.

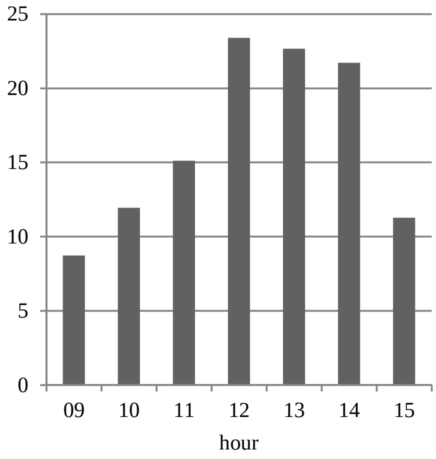


B.



Intraday average duration from 01.09.2013 to 17.10.2013 (A) and from 17.02.2014 to 04.04.2014 (B)

A.



B.

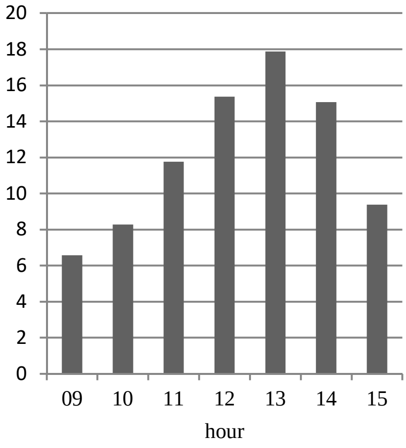
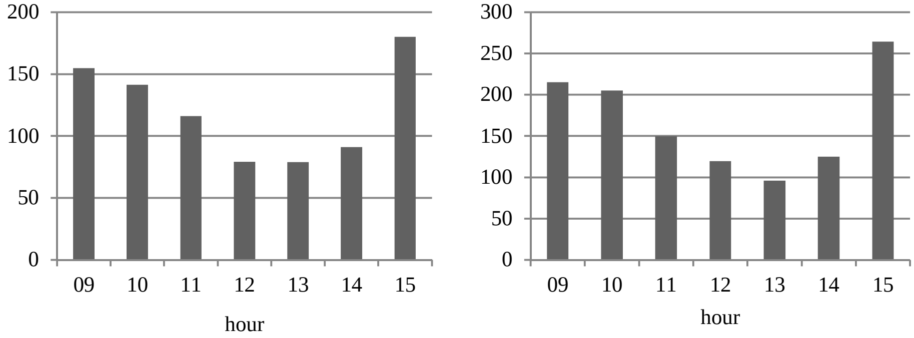


Figure 3 continued

Intraday average volume from 01.09.2013 to 17.10.2013 (A) and from 17.02.2014 to 04.04.2014 (B)

A. **B.**



Source: own calculations.

For XOM, the average absolute returns and average volumes for both periods exhibit a typical U-shape that characterizes normal cycle of investors' activities on the market. For duration, the inverse U-shape is observed that correspond to the typical characteristics. The increased activity is observed not only in the first but also in the second and third hours of the trading day.

Figure 4 presents the autocorrelation function (ACF) for price duration and volume. Its shape is typical for stationary processes (see: Box and Jenkins, 1970). Note that for both shares, duration characterizes longer memory than trading volume. The values of ACF for ALFT (duration) are greater than in the case of XOM.

Figure 4. Duration and volume (after cyclical adjustment)

ALFT XOM

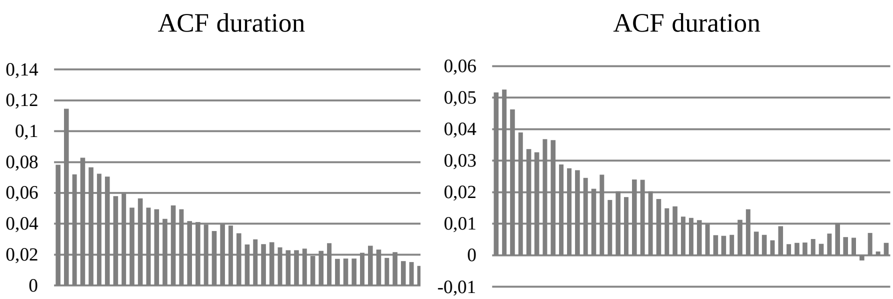
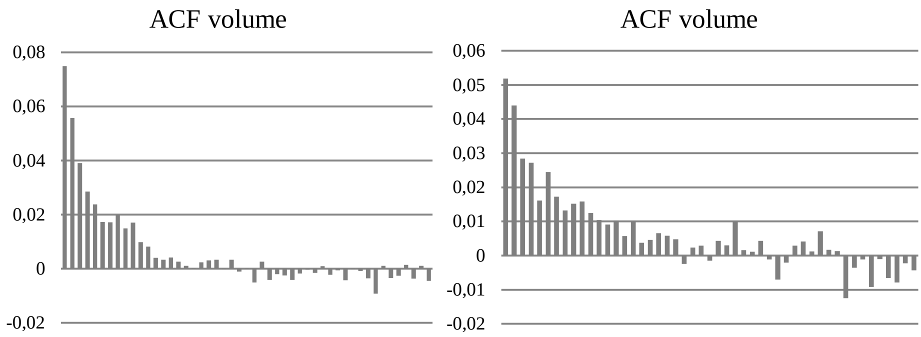


Figure 4 continued



Source: own calculations.

Empirical Results

After eliminating the cyclical patterns from the data, the models described in section III are estimated. The first AR(1)-EGARCH (1,1) model including the impact of price and volume duration in both equations is estimated. The form of the model, corresponding to formula (1), is as follows:

$$r_t = a_0 + a_1 r_{t-1} + b_1 d_{t-1} + b_2 w_{t-1} + \nu_t$$
$$\nu_t = \sigma_t \varepsilon_t$$
$$\varepsilon_t \sim \text{i.i.d. (t-skew(}\upsilon,\lambda))$$
$$ln\sigma_t^2 = \omega + \beta_1 ln\sigma_{t-1}^2 + \gamma(\varepsilon_{t-1}) + \alpha_1\gamma(\varepsilon_{t-2}) + \rho_1 d_{t-1} + \rho_2 w_{t-1}$$

where d_{t-1} denotes price duration and w_{t-1} denotes volume duration.

As indicated in the formula above, a skewed t-Student error distribution is assumed. In this section, the results of estimation are presented, focusing mainly on the impact of both price and volume duration on the observed volatility of returns. That is why presentation of parameters' estimates for the first equation is limited to only two companies (Table 5). The estimates of the conditional variance equation are given for all companies in Table 6. In each table the period 01.09.2013 until 17.10.2013 is denoted as I, and the period between 17.02.2014 until 04.04.2014 as II.

Table 5. Estimates of the conditional mean equation (r_t)

Company name	Period	a_0	a_1	b_1	b_2
ALFT	I	-0.03082	0.08164	0.00664	0.01739
		(-0.01049)	(0.00543)	(0.00538)	(0.00576)
	II	0.03349	-0.37773	-0.00795	-0.02770
		(0.0053)	(0.00377)	(0.00231)	(0.00247)
XOM	I	-0.00171	0.12830	-0.01126	0.00877
		(0.01435)	(0.00946)	(0.0081)	(0.00791)
	II	-0.01037	0.12022	0.00232	0.00301
		(0.00691)	(0.00386)	(0.00369)	(0.00356)

Source: own calculations.

The main information coming from the results of estimating eq. (r_t) is that both price and volume duration are significant only for ALFT, except for the price duration in period I. It is interesting that the there is a change of signs for the corresponding parameters b_1 and b_2. In the case of the Russian company ALFT, the change is from positive sign to negative one. This may indicate that the greater volume is related with sells of the shares. The worsening of the political sentiment causes an increase in the activity of investors who mainly sold their assets, decreasing their returns. For the American company, XOM, the price and volume duration estimates are insignificant.

Table 6. Parameter estimates of the equation $\ln\sigma_t^2$

Company name	Period	ω	ρ_1	ρ_2	Alpha	Gamma	Beta
Shares from Russian market							
ALFT	I	-0.22340	-0.01941	0.04211	0.43268	-0.06513	0.71000
		(0.02517)	(0.01179)	(0.00846)	(0.03565)	(0.02181)	(0.03031)
	II	-0.27742	-0.01204	0.03402	0.41768	0.01164	0.83847
		(0.00562)	(0.00237)	(0.00186)	(0.00807)	(0.00508)	(0.00471)
ROSN	I	0.17094	0.00293	0.11752	1.88046	0.11067	0.65691
		(0.28077)	(0.02632)	(0.02572)	(0.59845)	(0.16087)	(0.08032)
	II	1.58890	-0.01809	0.06973	11.96600	0.52780	0.64114
		(0.19198)	(0.01048)	(0.00924)	(2.81046)	(0.24492)	(0.02218)

Table 6 continued

Company name	Period	ω	ρ_1	ρ_2	Alpha	Gamma	Beta
Shares from Russian market							
RTKM	I	-0.31506	-0.01249	0.07380	0.41079	0.02481	0.83546
		(0.02509)	(0.01378)	(0.00626)	(0.02313)	(0.01869)	(0.01785)
	II	-0.37802	-0.01657	0.04698	0.55863	0.04493	0.87810
		(0.00924)	(0.00347)	(0.00303)	(0.01374)	(0.00631)	(0.00709)
YNDX	I	0.23001	0.00021	0.00011	0.20613	0.07226	0.76863
		(0.0000)	(0.0000)	(0.0000)	(0.01648)	(0.02772)	(0.02994)
	II	0.21355	0.00034	-0.04466	0.16631	-0.02359	0.40272
		(0.07027)	(0.01711)	(0.01948)	(0.03638)	(0.02279)	(0.13012)
CTCM	I	0.09433	0.00869	-0.06129	0.19972	-0.05288	0.41884
		(0.09172)	(0.03067)	(0.07031)	(0.09717)	(0.04961)	(0.31876)
	II	0.02967	0.20469	-0.01282	0.1784	-0.02024	-0.02228
		(0.06483)	(0.02114)	(0.02168)	(0.04244)	(0.02534)	(0.09394)
Shares from American market							
MCD	I	-0.00989	0.00461	-0.03656	0.10409	-0.00425	0.87859
		(0.01744)	(0.00882)	(0.01135)	(0.02243)	(0.00973)	(0.05151)
	II	-0.02408	-0.01674	-0.02848	0.14226	0.00149	0.88516
		(0.00824)	(0.00384)	(0.00462)	(0.00911)	(0.00498)	(0.01152)
MSFT	I	-0.04690	-0.02730	0.01898	0.14595	0.00473	0.82581
		(0.01481)	(0.00832)	(0.01114)	(0.03893)	(0.00642)	(0.07446)
	II	-0.08713	-0.02151	0.02204	0.15489	-0.00123	0.85709
		(0.00897)	(0.00413)	(0.00463)	(0.01238)	(0.00567)	(0.02315)
YAHOO	I	-0.23386	0.14082	0.1206	0.12657	-0.13611	0.51778
		(0.07361)	(0.03291)	(0.04818)	(0.05096)	(0.02871)	(0.10805)
	II	-0.19309	0.02187	0.01181	0.19764	-0.01257	0.98744
		(0.0064)	(0.00084)	(0.00283)	(0.0069)	(0.00448)	(0.00121)
XOM	I	-0.10215	-0.01003	-0.01534	0.18486	0.00066	0.92220
		(0.01269)	(0.0043)	(0.00516)	(0.0217)	(0.00707)	(0.01647)
	II	-0.06985	-0.01076	0.00215	0.11710	-0.00678	0.94856
		(0.00373)	(0.00165)	(0.00175)	(0.00491)	(0.00258)	(0.00363)

Source: own calculations.

For the case of volatility, one observes a diverse impact of price and volume duration on volatility. For many company shares, i.e., ROSN, RTKM, MSFT and YAHOO, the volume duration exhibited positive and significant impact for volatility in both periods. It is typical for liquid assets when investors are rather careful. Negative impact of volume duration is observed in the case of XOM, which characterizes the typical situation for a significant ratio of informed investors trading in the market. In case of ALFT (I period), MSFT and CTCM (both periods) the impact of volume durations are insignificant.

However, there is negative impact of price duration for volatility, observed for ROSN (II period) and RTKM (both periods) which suggests a decreasing number of individual investors (see, Admati & Pfleiderer, 1988). Their risk aversion is then growing. Thus periods of high volatility correspond to longer time of price duration and low volumes of transactions. When the longer duration implied decrease in volatility, the Eslaey and O'Hara rule may hold that namely, no trade means no news (Easley & O'Hara, 1992). Thus, it is worth mentioning that the gamma parameter responsible for asymmetry of reaction for good and bad news for in the EGARCH model is significant in the following cases: ALTF (both periods), ROSN and RTKM (II period), YNDX (I period), YAHOO (both periods) and XOM (II period). For the remaining assets, it is insignificant, in line with Easley and O'Hara. In the case of AR(1)-EGARCH(1,1) models, it is hard to indicate the positive or negative impact of the Ukrainian crisis for returns volatility. The results are rather diversified.

In the next stage of the research, separate models for price and volume durations, i.e., ACD and ACV models, are estimated. The reason is to test whether the dynamics in both periods for all shares are typical or not. The parameter estimates are given in Table 7 (for the ACD model) and Table 8 (for the ACV model). The estimation is done by Dobrzyński in R using algorithm prepared in 2011 and popularized by Tsay (http://faculty.chicagobooth.edu).

Table 7. Estimated ACD models

Company name	Period	Omega	Alfa	Beta	Shape
ALFT	I	0.0958	0.1303	0.7727	0.7713
		(0.0321)	(0.0163)	(0.0418)	(0.0079)
	II	0.0391	0.0957	0.8663	0.9243
		(0.0019)	(0.0026)	(0.0038)	(0.0025)

Table 7 continued

Company name	Period	Omega	Alfa	Beta	Shape
ROSN	I	0.0363	0.1115	0.8551	0.9864
		(0.0026)	(0.0042)	(0.0056)	(0.0038)
	II	0.0639	0.1235	0.815	0.9606
		(0.0026)	(0.0031)	(0.0048)	(0.0023)
RTKM	I	0.0406	0.1418	0.8223	0.8819
		(0.0048)	(0.0085)	(0.0106)	(0.006)
	II	0.0581	0.1073	0.8349	0.8593
		(0.0027)	(0.0032)	(0.005)	(0.0024)
YNDX	I	0.1478	0.1154	0.737	0.8548
		(0.0477)	(0.0175)	(0.0571)	(0.0095)
	II	0.1325	0.091	0.7769	0.8666
		(0.0136)	(0.0058)	(0.0177)	(0.0033)
CTCM	I	0.1178	0.1094	0.7687	0.8344
		(0.0367)	(0.0215)	(0.0431)	(0.0125)
	II	0.0825	0.0921	0.8169	0.8976
		(0.0156)	(0.0062)	(0.0217)	(0.0073)
MCD	I	0.1824	0.0836	0.734	0.9427
		(0.0333)	(0.0108)	(0.041)	(0.0071)
	II	0.1235	0.063	0.8134	0.9558
		(0.013)	(0.0046)	(0.0161)	(0.0039)
MSFT	I	0.1823	0.0836	0.7341	0.9428
		(0.0333)	(0.0108)	(0.041)	(0.0071)
	II	0.1232	0.061	0.8135	0.9557
		(0.013)	(0.0046)	(0.0161)	(0.0039)
YAHOO	I	0.0254	0.0778	0.8831	0.9591
		(0.0428)	(0.034)	(0.0035)	(0.0182)
	II	0.0376	0.0576	0.9051	0.961
		(0.0025)	(0.0022)	(0.004)	(0.0029)

Table 7 continued

Company name	Period	Omega	Alfa	Beta	Shape
XOM	I	0.0866	0.054	0.8592	0.93
		(0.015)	(0.007)	(0.0208)	(0.0057)
	II	0.0711	0.0688	0.8605	1.0005
		(0.0044)	(0.0027)	(0.0063)	(0.0028)

Source: own calculations.

The ACD models indicate that a relatively high reaction for new information (alfa>0.1) is observed for all companies' shares quoted on the MOEX market that exhibited greater sensitivity for news than the shares quoted on the NYSE or the NASDAQ. The increasing beta for period II as compared with period I indicates that that the share of individual investors in the market decreases..

High (and greater in period II) level of shape coefficient from the Weibull's distribution is related to the fact of increased number of transactions in period II, which is characteristics for the Russian shares quoted on the MOEX. When the market is more liquid, the share of outliers in the sample is relatively smaller.

Except for the MSFT, the American companies' shares are characterized by higher persistence (represented by beta) and greater resistance for outliers (according to the shape parameter). The increase of beta in period II suggests that the impact of individual investors has been weakened. Comparing shares quoted on the NASDAQ and the NYSE indicates no important differences between the markets.

Table 8. Estimated ACV models

Company name	Period	Omega	Alfa	Beta	Shape
ALFT	I	0.1714	0.0832	0.6888	0.6181
		(0.0681)	(0.0161)	(0.0818)	(0.0061)
	II	0.1236	0.0855	0.7758	0.6887
		(0.0103)	(0.0035)	(0.0132)	(0.0017)
ROSN	I	0.0801	0.131	0.7663	0.6033
		(0.0175)	(0.0087)	(0.026)	(0.0025)
	II	0.0815	0.108	0.7924	0.5985
		(0.0106)	(0.0047)	(0.0148)	(0.0015)

Table 8 continued

Company name	**Period**	**Omega**	**Alfa**	**Beta**	**Shape**
RTKM	I	0.1759	0.1423	0.6648	0.6066
		(0.0325)	(0.0151)	(0.0445)	(0.0042)
	II	0.1386	0.0932	0.753	0.6098
		(0.01)	(0.0048)	(0.0145)	(0.0018)
YNDX	I	0.2069	0.0292	0.7679	1.0584
		(0.0709)	(0.0101)	(0.0739)	(0.0109)
	II	0.1919	0.0333	0.7700	1.0423
		(0.1129)	(0.0173)	(0.1199)	(0.0252)
CTCM	I	0.1561	0.0396	0.7891	1.0114
		(0.0612)	(0.0081)	(0.0559)	(0.0149)
	II	0.1422	0.0413	0.8112	1.0213
		(0.1349)	(0.0133)	(0.1239)	(0.0262)
MCD	I	0.0763	0.0457	0.8765	1.1279
		(0.016)	(0.0059)	(0.021)	(0.0044)
	II	0.1972	0.0421	0.7932	1.2262
		(0.0242)	(0.0038)	(0.0261)	(0.0046)
MSFT	I	0.0763	0.0457	0.8765	0.7679
		(0.016)	(0.0059)	(0.021)	(0.0044)
	II	0.1333	0.049	0.8167	0.8826
		(0.0121)	(0.003)	(0.0142)	(0.0028)
YAHOO	I	0.1355	0.0495	0.8156	0.9766
		(0.0903)	(0.0216)	(0.1047)	(0.021)
	II	0.1075	0.0539	0.8383	0.967
		(0.0091)	(0.0029)	(0.0113)	(0.0028)
XOM	I	0.096	0.0444	0.8603	1.0969
		(0.0167)	(0.005)	(0.0198)	(0.0066)
	II	0.1524	0.0491	0.8003	1.1407
		(0.0135)	(0.0029)	(0.0154)	(0.003)

Source: own calculations.

Volume size is considered as a good proxy of information flow. However, it is often distorted by a random noise. Analyzing the estimated ACV models, several observations can be ascertained. First, the conditional volume duration is more sensitive for new information flows in the case of shares from the MOEX market. Second, the persistence of these shares is lower than in the case of price duration. Third, the shape coefficient is much lower for Russian shares than for the ACD models and in the case of American shares it supports the fact that their liquidity on the market is low. In the second period, the increasing number of transactions with the Russian shares indicates rapid changes in trade. The American shares are highly persistent. It may be due to a small number of individual investors or their disregard of the news. The betas for the shares quoted on the MOEX are smaller in magnitude while the alfas are higher. Similar differences are observed for the ACD models. When the results for YNDX and CTCM are analyzed, one needs to take into account that they join the characteristics of both the Russian and American markets. They exhibit a small impact of new information typical for the NASDQ and NYSE, but the level of persistence is significantly lower.

In the last stage of the empirical analysis, the Manganelli models are estimated. These models incorporate all the information that is individually analyzed in the previous models. The model (4) is estimated in the following form:

$$\psi_t = p_0 + p_1\psi_{t-1} + p_2 w_{t-1} + p_3 d_{t-1} + p_4 y_{t-1}^2 + \varepsilon_t^{\psi}$$
$$v_t = q_0 + q_1 v_{t-1} + q_2 w_{t-1} + q_3 d_{t-1} + q_4 y_{t-1}^2 + \varepsilon_t^{v}$$

The results are presented in Table 9.

Table 9. Estimated Manganelli models

AFLT					
Period	p_0	p_1	p_2	p_3	p_4
I	**0.9278**	**0.8867**	-0.0003	**0.0812**	-0.0004
	(0.0122)	(0.0063)	(0.0005)	(0.0007)	(0.0015)
II	**0.9206**	**0.8030**	**-0.0082**	**0.0615**	0.0000
	(0.0036)	(0.0067)	(0.0009)	(0.0022)	(0.0000)

Table 9 continued

			AFLT		
Period	p_0	p_1	p_2	p_3	p_4
I	**0.8963**	**0.751**	**0.0569**	**0.002**	**0.0278**
	(0.0041)	(0.0093)	(0.0003)	(0.0005)	(0.001)
II	**0.7818**	**0.7179**	**0.0320**	**-0.0109**	0.0000
	(0.004)	(0.0095)	(0.0026)	(0.0016)	(0.0000)
			ROSN		
Period	p_0	p_1	p_2	p_3	p_4
I	**0.9564**	**0.9662**	0.0001	**0.0642**	0.0000
	(0.0183)	(0.0014)	(0.0002)	(0.0003)	(0.0000)
II	**0.9406**	**0.9482**	**-0.0000**	**0.0739**	**0.0002**
	(0.0081)	(0.0011)	(0.0001)	(0.0002)	(0.0000)
Period	q0	q1	q2	q3	q4
I	**0.9387**	**0.9114**	**0.0703**	-0.0006	**0.0000**
	(0.0112)	(0.0023)	(0.0003)	(0.0005)	(0.0000)
II	**0.9396**	**0.8914**	**0.0659**	0.0006	0.0012
	(0.0046)	(0.0016)	(0.0002)	(0.0002)	(0.0000)
			RTKM		
Period	p_0	p_1	p_2	p_3	p_4
I	**0.9539**	**0.9513**	0.0005	**0.0864**	-0.0006
	(0.0297)	(0.0029)	(0.0004)	(0.0006)	(0.0007)
II	**0.9524**	**0.9559**	**-0.0007**	**0.0632**	0.0000
	(0.0113)	(0.0013)	(0.0001)	(0.0002)	(0.0000)
Period	q0	q1	q2	q3	q4
I	**0.8888**	**0.8799**	**0.0782**	**-0.0018**	**0.0283**
	(0.0121)	(0.0045)	(0.0005)	(0.0007)	(0.0007)
II	**0.9641**	**0.927**	**0.0456**	**-0.0018**	**0.0001**
	(0.0081)	(0.0016)	(0.0002)	(0.0003)	(0.0000)
			YNDX		
Period	p_0	p_1	p_2	p_3	p_4
I	**0.8475**	**0.8597**	**-0.0038**	**0.0776**	**0.0505**
	(0.0104)	(0.0075)	(0.0006)	(0.0007)	(0.0041)
II	**0.9389**	**0.8439**	-0.0008	**0.0747**	**0.0002**
	(0.0064)	(0.0029)	(0.0006)	(0.0002)	(0.0000)

Table 9 continued

			AFLT		
Period	p_0	p_1	p_2	p_3	p_4
I	**1.0082**	**0.8499**	**0.0226**	**0.0010**	**-0.0189**
	(0.0031)	(0.0078)	(0.0002)	(0.0002)	(0.0013)
II	**0.9496**	**0.8755**	**0.0514**	**-0.0003**	0.0000
	(0.0026)	(0.0026)	(0.0002)	(0.0001)	(0.0000)
			CTCM		
Period	p_0	p_1	p_2	p_3	p_4
I	**0.8821**	**0.8347**	**-0.0068**	**0.0682**	**0.0612**
	(0.0114)	(0.0081)	(0.0012)	(0.0009)	(0.0061)
II	**0.8387**	**0.8568**	**-0.0002**	**0.0757**	**0.0009**
	(0.0124)	(0.0056)	(0.0008)	(0.0006)	(0.0000)
Period	q0	q1	q2	q3	q4
I	**0.9983**	**0.8233**	**0.0326**	**-0.0011**	**-0.0147**
	(0.0431)	(0.0061)	(0.0012)	(0.0007)	(0.0013)
II	**0.9697**	**0.8455**	**0.0424**	**-0.0009**	**0.0002**
	(0.0127)	(0.0066)	(0.0008)	(0.0004)	(0.0000)
			MCD		
Period	p0	p1	p2	p3	p4
I	**0.6822**	**0.884**	**-0.0055**	**0.0595**	**0.1827**
	(0.0074)	(0.0048)	(0.0005)	(0.0004)	(0.0038)
II	**0.8962**	**0.9288**	**-0.0025**	**0.0396**	**0.0444**
	(0.0039)	(0.002)	(0.0002)	(0.0002)	(0.0008)
Period	q0	q1	q2	q3	q4
I	**1.0154**	**0.8451**	**0.0262**	-0.0002	**-0.0287**
	(0.0025)	(0.0055)	(0.0002)	(0.0001)	(0.0014)
II	**0.9812**	**0.9025**	**0.0252**	**-0.0009**	**-0.0047**
	(0.0015)	(0.0024)	(0.0001)	(0.0001)	(0.0004)
			MSFT		
Period	p0	p1	p2	p3	p4
I	**0.9283**	**0.9132**	**-0.0008**	**0.0526**	**0.0163**
	(0.0071)	(0.0031)	(0.0003)	(0.0003)	(0.0004)
II	**1.0012**	**0.8621**	**-0.0009**	**0.0002**	**-0.0001**
	(0.002)	(0.0021)	(0.0002)	(0.0001)	(0.0002)

Table 9 continued

			AFLT		
Period	q0	q1	q2	q3	q4
I	**0.9746**	**0.9615**	**0.0246**	**0.001**	**0.001**
	(0.009)	(0.0021)	(0.0002)	(0.0001)	(0.0002)
II	**0.9984**	**0.9267**	**0.0044**	-0.0002	-0.0001
	(0.0047)	(0.0016)	(0.0002)	(0.0002)	(0.0002)
			YAHOO		
Period	p0	p1	p2	p3	p4
I	**0.9431**	**0.9615**	0.0011	**0.0231**	**0.0229**
	(0.0274)	(0.0077)	(0.0007)	(0.0006)	(0.0039)
II	**0.919**	**0.9615**	**-0.0007**	**0.0344**	**0.0346**
	(0.0089)	(0.0019)	(0.0002)	(0.0002)	(0.0004)
Period	q0	q1	q2	q3	q4
I	**0.9813**	**0.9301**	**0.0301**	**-0.0011**	-0.0052
	(0.0149)	(0.0103)	(0.0007)	(0.0005)	(0.0037)
II	**0.9705**	**0.928**	**0.0253**	**0.0013**	**0.0022**
	(0.0034)	(0.0026)	(0.0001)	(0.0001)	(0.0003)
			XOM		
Period	p0	p1	p2	p3	p4
I	**0.9724**	**0.885**	0.0000	**0.0292**	0.0000
	(0.0052)	**(0.0039)**	(0.0000)	**(0.0000)**	(0.0001)
II	**0.9154**	**0.9546**	**-0.0012**	**0.0417**	**0.0322**
	(0.0052)	**(0.0012)**	**(0.0001)**	**(0.0001)**	**(0.0004)**
Period	q0	q1	q2	q3	q4
I	**0.9768**	**0.8994**	**0.0234**	0.0000	0.0000
	(0.0038)	**(0.0037)**	**(0.0000)**	(0.0000)	(0.0000)
II	**0.9662**	**0.9159**	**0.03**	**-0.0012**	**0.0018**
	(0.0017)	**(0.0016)**	**(0.0001)**	**(0.0001)**	**(0.0003)**

Source: own calculations.

On the basis of Table 9, note that for all shares quoted on the MOEX similar relationships are observed. Particularly, it shows a positive impact from the observed price duration on the expected price duration and a similar impact for volume duration. This is typical for such type of analysis (Doman & Doman 2010). In both periods, volatility does not affect expected price duration. It indicates a relatively low activity of non-informed investors. It is accompanied by a high level of risk aversion for an average individual investor.

The results of volume durations are interesting. For the first period, a significant impact of volatility exists, which however disappeared in the second period. For the second period, the same results as for the price duration are confirmed. Disappearance of the volatility in the second period supports the hypothesis that the Ukrainian crisis had a negative impact on the Russian stock market. The crisis weakened a small group of individual investors operating on the MOEX market. Furthermore, note the negative impact of volume on price duration that occurred during the Ukrainian crisis. It can be considered together with the negative impact of volume on the return that happens when the investors react on bad news.

However, the impact of price duration on volume is either negative or none. When shares quoted on the Russian market are compared with the American shares, the most significant difference concerns the impact of volatility on price and volume duration. For stock quoted on NASDAQ and NYSE, this relationship is significant with a positive sign. In the second period, it is stronger than the first one. The reason is increased investors' uncertainty and thus greater cautious in new transactions making. The estimated relationships between volatility and expected volume duration are difficult to interpret. However, their appearance provides some information that possibly different groups of investors have different investment goals and investment horizons. The informed investors have better access to information. The others, those who are more risky make their decisions upon their beliefs about the incoming news. They are likely to exhibit some behavioral heuristics. Their decisions are finally the source of information for the other investors that is supported by the significant impact of volatility on both price and volume duration. Negative impact from volume on the price duration indicates that greater transactions result in occurrence the subsequent transactions with greater frequency. Investors are encouraged to make their transactions.

When two Russian shares quoted on the NASDAQ and NYSE are analyzed, i.e., YNDX and CTCM, similar conclusions are reached. In the second period, one observes two important differences. First, the impact of volatility on price and volume duration is lower. This is due to the fact that investors withdrew from this segment of the market because these companies operate mainly in Russia. Second, is the significant, but weaken relationship, between the observed (lagged) volume and expected price duration as well as the observed (lagged) duration and expected volume. It might be related with the distortion of hitherto flow of information and the way investors react. It seems that in the decision-making process, the investors disregard the magnitude of transactions and their frequency. Thus, the trade on the stock market became more chaotic and unpredictable.

Conclusions

The paper compares two different periods – before and after the Ukrainian political crisis at the beginning of 2014 from the perspective of market microstructure. Data from the mature American and the Russian emerging stock markets are used. The hypothesis is that the crisis influenced the fragile Russian financial market equilibrium. As markets adapt to the new equilibrium, the paper studies the effects of the Ukrainian crisis and the imposition of economic sanctions on Russia. The paper investigates the relationships between volatility, duration, price and volume for selected joint stock companies listed on the United States (U.S.) and the Russian stock markets. These markets are the New York Stock Exchange (NYSE), the National Association of Securities Dealers Automated Quotations System (NASDAQ) and the Moscow Stock Exchange (MOEX). Furthermore, the study compares the microstructure effects of the first phase of the Ukrainian crisis (from February 17, 2014 until April 4, 2014) and a more neutral period of the same length (from September 1, 2013 until October 17, 2013). Variety of econometric models for time series are applied. These econometric models are the EGARCH(p,q), ACD, ACV and Manganelli. The paper shows that the MOEX has no good transmission channel from informed investors to the rest of the market. At the same time, the results for the United States companies' shares are in line with the expectations for mature market where large groups of different investors trade in the stock markets.

The paper reveals that as a result of the Ukrainian – Russian conflict the MOEX market exhibits a significant increase in the number of transactions, which resulted in shorter duration and increased volume. The paper attributes these changes to the economic sanctions which were imposed on Russia at the beginning of the Ukrainian crisis. These characteristics have not changed for the U.S.

Typical intraday cyclical patterns for duration and volume are observed for both the NYSE and the MOEX. For the MOEX market, the U-shape pattern is flatter. The autocorrelation patterns are typical for ultra-high frequency data. In the case of the estimated ACD models for Russian companies, the impact of new information on expected duration is observed whereas it is not confirmed for the U.S.

However, the companies with shares listed on the American stock markets are characterized by a higher persistence, typical for mature markets. Lower values of shape parameter in the Weibull distribution for the Russian companies are caused by larger number of non-typical observations resulting in lower market stability. Using the ACV models, the increase in the persistence parameter for the second period is significant for all companies.

The estimation of Manganelli model allows for a more precise interpretation. It shows that the MOEX has no appropriate transmission channel from informed investors to the rest of the market. This is due to the lack of the impact of volatility on the expected duration and/or volume and disappearing impact of other variables during the period of the Ukrainian crisis.

At the same time, the results for the U.S. companies, the reactions of the stock markets are in line with the expectations for mature market where large groups of different investors are present. When trade of the Russian shares traded on the NYSE and NASDAQ has been analyzed for the year 2013, they are similar to the behavior of typical American shares. At the beginning of the Ukrainian crisis, the situation has changed because the impact of duration and volume disappeared, which indicates that the inflow of information has changed.

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