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HERDING BEHAVIOUR IN AN EMERGING MARKET: EVIDENCE FROM MOSCOW EXCHANGE

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Abstract

The current research is motivated by a growing amount of evidence on behavioural biases, contradicting propositions of Efficient Market Hypothesis. The authors of the paper focus particularly on examining herding towards the market– a type of investor behaviour, which leads investors to mimic each other's actions and results in lower-than-efficient dispersion of asset returns. This paper focuses on establishing whether herding exists in Russian stock market, and analyses the factors potentially associated with its emergence. Contrary to most of the studies in the field, the authors differentiate between rational and irrational forms of herding, and empirically show the importance of this distinction.

To study herding phenomenon in the context of Moscow Exchange, the authors study the relationship between market returns and dispersion of individual asset returns for the period of April 4, 2008 – December 30, 2015. The authors find evidence of regular herding in Moscow Exchange, especially during the days with negative market returns, extreme upward oil price movements and periods of turmoil, e.g. Financial Crisis of 2008 and annexation of Crimea in 2014. The authors also find significant evidence of spurious herding during the days of important macroeconomic news releases, sanctions announcements and high-liquidity days. No robust evidence is found on the association between herding and information environment around a company, proxied by its size and the number of analysts following it. The results presented in the paper shall be of particular interest for investors in stocks traded on Moscow Exchange and relevant regulatory institutions.

Key words: herding, Moscow Exchange, spurious herding, irrational herding

1. Introduction

Predicting or explaining stock market fluctuations has been the centre of interest for researchers, investors and relevant regulatory bodies in past decades. Over this time, two contradicting views on the underlying mechanisms of market behaviour have evolved. The first distinctive strand of research, which became known under the term Efficient Market Hypothesis (EMH), was formulated in the works of Sharpe (1964), Fama (1965), Jensen (1967), Fama (1970), etc. Its main idea postulates that markets behave efficiently and rationally, i.e. stock prices incorporate the information available on the market. Based on the degree of information inclusion, markets can be weakly, semi-strongly and strongly efficient. The ultimate conclusion one could derive from the EMH is that it is impossible to beat the market consistently, although one may be able to do so in any given period purely by chance.

Gradually, a body of empirical evidence mounted, which challenged the ideas of the Efficient Market Hypothesis. Among others, the evidence suggested a greater degree of variation in asset prices than efficient asset-pricing models could explain (LeRoy & Porter, 1981) and the existence of calendar effects (Rozeff & Kinney, 1976; Keim, 1983). To find explanations for these anomalies, researchers have switched to developing other theories, thus, forming a new branch of financial research – behavioural finance (Shiller, 2003).

Proponents of behavioural finance stipulate that there are certain obstacles to market efficiency that should be taken into account, e.g. limits to arbitrage (D'Avolio, 2002; Lamont & Thaler, 2003) and behavioural factors: myopic loss aversion among investors (Haigh & List, 2005); investors' self-attribution (Daniel, Hirshleifer, & Subrahmanyam, 1998); and diversification bias (Mauck & Salzsieder, 2015). The findings of researchers examining behavioural finance have several important implications. For instance, rational investors may not be able to always offset trades of less rational ones, hence, markets may deviate from an efficient state. Moreover, at times, rational investors tend to intentionally amplify these deviations by conducting transactions ahead of feedback traders (De Long, Shleifer, Summers & Waldmann, 1990). One of the possible outcomes of such actions is the formation of herding behaviour on the market.

Initially, herding is a phenomenon spotted from animals, which describes a behavioural pattern of gathering in groups to get protection from predators, find mates and food (Warner & Dyer, n.d.). The concept was applied to human interactions by Nietzsche (1886), and later Keynes (1936) used the notion in an economic context. Amongst growing concerns about the influence of behavioural factors on financial markets, herding gradually became studied within this field as well. In financial markets, there are several definitions of herd behaviour, which are rather similar in essence, but capture different herding manifestations. For instance, Bikchandani & Sharma (2001) define herding as a situation when investors ignore their common beliefs and mimic their peers; hence, the onus is placed on irrational aspects of this phenomenon. The authors of this paper employ a broader definition of herding that is used in academic literature on the issue. Herding is observed when "a group of investors trades in the same direction over a period of time" (Nofsinger & Sias, 1999; as cited in Chiang & Zheng, 2010, p.1911). Applying this definition, the authors look at both rational and irrational sides of herd behaviour. Hence, this paper aims at eliciting more evidence on the complex issue of herding and the factors associated with its emergence.

The authors choose to carry out the research on Moscow Exchange. The main reasons for choosing this geographical setting are the following. First of all, Russia has faced a period of austere political and economic challenges lately, accompanied by growing investor uncertainty. As argued by a number of researchers (Christie & Huang, 1995; Bikchandani & Sharma, 2001), such economic developments hamper financial markets and make the formation of herding more likely to occur. Secondly, despite being one of the world's biggest emerging economies, Russian stock exchange has the reputation of a market with relatively poor investor protection and prevailing information asymmetry (Corcoran, 2013; Iwasaki, 2014), which potentially might cause herding as well. It is peculiar, but in spite of these traits of Russian economy and financial markets in particular, there has been no research on the issue of herding in this geographical setting, to the best of the authors' knowledge.

Hence, this research paper investigates whether herding towards the market exists in Moscow stock exchange. Apart from that the authors also test the association between herd behaviour towards the market and a group of factors pertaining to calendar events, liquidity, information environment and oil price fluctuations. The authors formulate two research questions:

1) Is herding towards the market present in Moscow Exchange?
2) If present, what are the factors associated with its formation?

This research paper offers three main contributions to the existing body of literature. First of all, the authors distinguish between rational and irrational mechanisms underlying the formation of herds – an issue neglected in most of academic studies published on the topic. Moreover, the paper empirically illustrates the importance of the aforementioned distinction. Secondly, this study tests potential factors that affect the formation of herding in the context of an emerging market. The authors examine scarcely researched determinants, like number of analysts following a company and liquidity, as well as more profoundly discuss commonly tested aspects, like calendar effects of financial crises. By differentiating between rational and irrational herding components, the authors obtain novel evidence related to herding during periods of high-liquidity, macroeconomic news announcements and extreme oil price fluctuations. Finally, the paper enhances the body of knowledge on herding in emerging markets. As indicated in Section 2, most of the existing evidence of this phenomenon in this group of markets relates to Asian countries. Russia is a new and not-yet-studied area with this respect. The findings of the paper should be of particular interest to researchers exploring financial market efficiency; relevant regulatory bodies supervising financial markets in Russia; and investors, especially taking into account a renewed interest in Russian stock market worldwide (Namatalla & Gokoluk, 2016; Platt & Bullock, 2016).

The remainder of the paper is structured as follows. Section 2 presents a summary of evidence in academic literature on herding behaviour in financial markets. Section 3 elaborates on the methodology and dataset used in this paper. Section 4 presents empirical findings of the paper, while Section 5 provides their discussion and limitations of the current study. Section 6 concludes.

2. Literature Review

In this section, the authors present a review of existing literature on the issue of herding in financial markets. We start by defining and separating different types of herding behaviour: intentional and spurious (unintentional) herding. The authors then move on to review the most commonly used herding measures and describe results of their empirical implementation in existing literature. Finally, we discuss studies which aim at testing factors associated with herding.

2.1 Intentional vs. Spurious Herding

Scholarly literature describes two general types of herding that need to be distinguished: intentional and spurious (unintentional) herding. The difference between these two notions stems from contrasting underlying mechanisms. As defined by Bikchandani & Sharma (2001), intentional herding derives from a blatant willingness of market participants to replicate the actions of others. This type of herding presupposes that investors suppress their ideas and beliefs and purposefully mimic decisions of others following some market consensus. It may be both rational and irrational. According to Devenow & Welch (1996), irrational herding arises from psychological factors: investors might feel more safe and secure when following the crowd. DeLong, Shleifer, Summers & Waldmann (1990) suggest that irrational herds might also arise among unsophisticated investors who incorrectly interpret external information. These investors centre their trading behaviour around pseudo-signals, which are, in effect, just a noise. Shleifer & Summers (1990) argue that such signals usually spread fast among unsophisticated traders and lead them to herd on non-fundamental information. Rational herding, as summarized by Bikchandani & Sharma (2001), is likely to stem from other drivers: information asymmetry, reputation concerns and compensation concerns.

According to Bikchandani & Sharma (2001), information-based intentional herding, or information cascades, occurs when investors operate in an imperfect information environment. Understanding that the data at their disposal is not perfect, investors try to infer private information from behaviour of their peers and, hence, herd. Several papers study this behavioural patterns. Zhou & Lai (2009) present evidence of information-based herding in Hong Kong. Choi (2016) finds herding among online and offline investors in Korean stock market and concludes that it might be induced by information exchange between market participants.

As mentioned above, another reason for rational intentional herding is reputation concerns. Graham (1999) reports that an investment manager might be willing to herd with his peers when he lacks knowledge and skills or has high reputation concerns. One can argue that such type of herding stems from information asymmetry as well: in this case, the manager's employer or the he himself lacks objective information to assess investment manager's abilities. Hence, herding with others benefits such manager as it keeps his results in line with those of the peers. One of the most recent empirical studies on this issue is Casavecchia (2016), who finds reputation-based herding in a sample of US mutual funds.

Finally, Bikchandani & Sharma (2001) discuss one more incentive for rational herd behaviour: compensation concerns. As a matter of fact, investment fund managers may be remunerated based on their performance relative to their peers. In this case, managers may opt for herding: clearly, it limits their maximum compensation, but at the same time it ensures them against poor performance relative to the benchmark and, hence, against low remuneration. Several recent studies support this idea: for instance, Gümbel (2005) states that investment managers prefer herding to investing into assets with higher returns in order to receive a higher remuneration. Hedesström, Gärling, Andersson & Biel (2015) also show that performance-based bonuses induce greater levels of herding.

As mentioned above, intentional herding should be distinguished from spurious one. Bikchandani & Sharma (2001) define spurious herding as a situation when people take similar actions because they receive similar information. As suggested by Lakonishok, Shleifer & Vishny (1992), one reason for the existence of spurious herding lies in investors' exposure to identical market information. Receiving similar signals, market participants independently take similar actions.

To conclude, intentional herding is a result of a willingness of market participants to suppress their beliefs and replicate the behaviour of others. Intentional herding may be irrational and rational; the causes of the latter being information asymmetry, reputation concerns and compensation concerns. Irrational intentional herding arises from psychological biases that investors possess. Irrational herding may be treated as a sign of market inefficiency, as in its presence market participants suppress their beliefs and converge to the market-wide opinion instead of taking independent decisions. Spurious herding, on the other hand, is not an indication of market inefficiency, as in that case investors still act independently and rationally.

2.2 Measures of herding

The relevant literature focuses mainly on two dimensions of herd behaviour in financial markets. One strand of researchers explores herding among institutional investors, while another takes a broader view of financial markets and studies market-wide herding. In the following paragraphs, the authors give a brief summary of herding measures most widely used in the literature. We first start with a measure of institutional herding and then proceed with reviewing literature on market-wide herding measures.

As the term 'institutional herding' suggests, it captures the presence of behavioural mimicking among professional participants of financial markets, such as mutual funds, pension funds, etc. One of the fundamental studies examining institutional herding is the paper of Lakonishok, Shleifer, & Vishny (1992), which introduced a measure of this type of herding (further referred to as LSV measure) that has been rather extensively used in subsequent works. The paper traces herding using the information on trades conducted by pension funds. More specifically, the authors look at changes in funds' holdings of a particular stock. By comparing them and identifying the relative amount of funds taking similar positions in the market, the authors are able to assess whether there is herding between institutional investors at an individual stock level. One of clear advantages of LSV methodology is the ability to quantify herding and present it in a form of some coefficient. However, as argued by Hachicha, Amirat & Bouri (2010), this measure does not distinguish between spurious and intentional herding.

Additionally, it does not take into account trading volumes, which may lead to underestimating the extent of herding on the market.

Another stream of research on herding behaviour focuses on determining whether market-wide herding exists. This type of research is not centred around some particular group of investors, but rather looks at a broader market perspective. There are generally three recognized measures of market-wide herding in the current scholarly literature developed by Hwang & Salmon (2004), Christie & Huang (1995) and Chang, Korana & Cheng (2000).

To trace herding behaviour, Hwang & Salmon (2004) propose to evaluate asset betas. They point out to the fact that, contrary to conventional asset-pricing models' assumptions of beta being constant, the empirical evidence suggests otherwise: there is a significant variance in observed equity betas. Hwang & Salmon (2004) stipulate that part of this variance might be attributed to changes in fundamentals, like, for instance, change of an industry by a company. However, these events are considered rare and their probability to occur within a short time span – small. Hence, the persisting variance in observed betas is attributed to irrational behavioural factors, like herding. The main idea of Hwang & Salmon (2004) postulates that any observed beta can be decomposed into several parts: a "true" equilibrium beta and some contagion factor, which arises due to behavioural factors, like irrational herding. The authors use state space models and Kalman filter to extract and quantify the contagion factor from observed betas and to measure irrational herding.

Christie & Huang (1995) and Chang et al. (2000) propose to look at the dispersion of asset returns instead. Both papers argue that during periods of high uncertainty or market stress, returns of individual stocks within the market will be distributed more tightly around overall market returns. The authors capture this phenomenon by looking at the relationship between cross-sectional standard deviation, CSSD (in the methodology of Christie & Huang, 1995), cross-sectional absolute deviation, CSAD (in the methodology of Chang et al., 2000), and market returns.

While it is possible to verify the existence of market-wide herding using methodologies of Christie & Hwang (1995) and Chang et al. (2000), they do not allow to distinguish between spurious (or, rational) and irrational herding. Galariotis, Rong & Spyrou (2015) offer an extension to these methodologies, which allows to draw this distinction. A more detailed description of Christie & Hwang (1995) measure is presented in Appendix A. Chang et al. (2000) methodology, as well as modifications proposed by Galariotis et al. (2015), are presented in Section 3, as the authors apply these models in the current empirical research.

2.3 Empirical evidence

The following section describes empirical evidence on the issue of herding documented by researchers in the field. Consistent with the structure of the previous section, we first describe the findings pertaining to institutional herding followed by those related to market-wide herding.

Initially, the research on institutional herding was mainly focused on the US market. For instance, Lakonishok et al. (1992) use the sample of the US pension funds and find weak evidence of herding. Grinblatt, Titman & Wermers (1995) focus on studying the US mutual funds' behaviour and conclude that they indeed exhibit herding patterns. Wermers (1999) finds high levels of herding among growth-oriented US mutual funds as well. In parallel with a huge volume of studies on institutional herding in the US market, more papers looking at other countries have been published recently. For instance, Voronkova & Bohl (2005) document herding among Polish institutional investors, while Walter & Weber (2006) do so for German mutual funds. Shyu & Sun (2010) find evidence of herding behaviour among Taiwanese institutional investors. The authors document that the magnitude of such behaviour is inversely related to the size of a traded firm, which the authors attribute to existence of information cascades. Zheng, Lia & Zhu (2015) find significant buy-side herding among Chinese institutional investors, which is amplified in periods of turmoil.

The research in the field of market-wide herding has been more extensive and, at times, contradicting. Empirical studies focus mostly on the US and Asian markets and predominantly employ the methodology of Chang et al. (2000). First of all, Chang et al. (2000) themselves implement their model on the sample of the US, Hong Kong, Japanese, Taiwanese, and South Korean companies. The authors document significant degree of herding in emerging markets of South Korea and Taiwan, weak evidence in Japan and no evidence in the US and Hong Kong. Demirer, Kutan & Chen (2010) study Chinese market and conclude that herding is non-existent there. However, Tan, Chiang, Mason & Nelling (2008) examine Chinese dual-listed stocks and report evidence of herd behaviour. Chiang & Zheng (2010) carry out a comprehensive study of herding on the sample of 18 advanced and emerging economies all over the world. The authors report no herding in the US and Latin American markets; Asian markets, according to the authors, do exhibit a certain degree of herding in both up and down stages. Filip, Pochea & Pece (2015) find herd behaviour in CEE countries, except for Poland and Romania. Garg & Jindhal (2014) find no evidence of herding in Indian stock exchange during 2000-2012, while Poshakwale & Mandal (2014) claim to detect the presence of herding in this country during 1997-2012. Galariotis et al. (2015) differentiate between various underlying mechanisms of this phenomenon, splitting herd behaviour into spurious and irrational parts. The authors find no evidence of either herding type in the US and the UK market on a regular basis.

The list of papers using the methodology of Hwang & Salmon (2004) includes smaller number of studies. Hwang & Salmon (2004) test their model on the US and South Korean stock markets and find evidence of herding in both up and down markets. Khan, Hassairi & Viviani (2011) study four developed European markets – France, UK, Germany and Italy – and conclude that herding is present in all of them. Demirer, Kutan, & Chen (2010) document herding in Taiwanese stock market, which is especially pronounced during down days. Guvercin (2016) looks at Egyptian and Saudi Arabian markets and finds that herding is present in Egypt only, while Saudi Arabian market does not exhibit such behaviour.

To conclude the subsection, one can observe that herding has been rather extensively researched in the US, Asia and some other emerging markets. The evidence collected indicates that developed markets show less herding than emerging ones. However, it is crucial to notice that reports on this phenomenon in emerging markets are at times contradicting. What is more, even developed markets are not universally free of herd formations, as several findings do report significant evidence of this behaviour there. As a matter of fact, the authors of this paper find no works examining herding in Russian stock market. Additionally, only two papers (Galariotis et al., 2015; Dang & Lin, 2016) draw the wedge between different underlying factors of herd formations. At the same time, as we show further in the study, failure to do so might lead to misinterpretation of results.

2.4 Factors associated with herding towards the market

Among the most common factors tested for association with herding are periods of financial turmoil, which are believed to be accompanied by higher uncertainty. Evidence with this respect is at times contradicting. For instance, Chiang & Zheng (2010) report signs of herding in the country, where the crisis originated, and claim that big crises have negative external repercussions causing herding in markets, which usually do not exhibit it (like, the US). Galariotis et al. (2015) support this proposition indicating that herding is pronounced during the Subprime crisis in the US and during Asian crisis of 1997-1998 in the UK. At the same time, a number of papers (e.g. Khan et al., 2011) find that the magnitude of herding decreases during turmoil.

Tests for calendar effects are not limited to periods of financial turmoil. For instance, Galariotis et al. (2015) test the impact of important news announcements on herding and find significant evidence of this phenomenon for the US during these days. Herding around important US news announcements is found to be present in France, Switzerland, Portugal, Greece and Germany by Belgacem & Lahiani (2013). Moreover, Belgacem & Lahiani (2013) point out that investors in Belgium, Finland and Ireland only herd on US news releases and do not exhibit herding with respect to any domestic factor. Gavrilidis, Kallinterakis, & Tsalavoutas (2015) study herding and Ramadan effects in a sample of Muslim countries. The authors conclude that for most countries in the sample, herding is amplified during Ramadan days. Demir & Solakoglu (2016) look at the influence of military actions on herding. The authors find little evidence of herding being driven by military interventions in Syria and Egypt.

Apart from the aforementioned factors, rather common are tests for herding spill-overs from foreign financial markets and investor uncertainty, usually proxied by Volatility Index (VIX) or its country-specific analogues. With respect to the first factor, Chiang & Zheng (2010) find that the US stock market developments tend to be a significant contributor to herding in non-US markets. Further, Yang & Chen (2015) find that herding activity in China and Taiwan is negatively related to herding in the USA. Balcilar, Demirer & Hammoudeh (2014) estimate the impact of uncertainty on herding and find a significant relationship between herding and VIX. Cakan & Balagyozyan (2016) apply volatility for sectoral analysis and find its impact only on financial, service, and technology sectors.

Additionally, oil price is considered to be one of potential herding determinants for resource-exporting countries. The relationship between its price and herding is tested by Balcilar et al. (2014) and Demir & Solakoglu (2016). The authors find that oil price fluctuations are correlated with herding formation in the US and Qatar.

As herding implies a significant number of investors trading in the same direction, this phenomenon should be associated with increased liquidity. At the same time the relationship between market-wide herding and liquidity hasn’t been broadly examined. To the best of the authors’ knowledge, there have been two researches devoted to examination of the relationship between market-wide herding and market liquidity. Galariotis, Krokida & Spyrou (2016) found herding at the time of high liquidity to prevail in developed markets of the US and the UK, Lam & Qiao (2015) find herding during high-trading-volume days in Hong Kong.

Apart from the aforementioned factors, some researchers include company-specific determinants into their models. For instance, it is widely believed that the amount and quality of information about a particular company affect its price. One of the proxies used to capture information availability is a company's size: the larger the company, the easier it should be to obtain credible information about it. With this respect, Chang et al. (2000) find no impact of size on herding patterns, while Thirikwa (2015) and Özsu (2015) report that firms with small market capitalization are associated with larger amount of herding behaviour. According to the authors, this might be an indication that investors struggle to obtain enough relevant information about these companies.

To conclude the section, there is no universal agreement on a complete list of factors associated with herding formation, although empirical literature devotes more attention to effects of crises and uncertainty. However, the results of these tests are at times contradicting. Additionally, the existing body of literature currently pays little attention to other factors potentially associated with herding, such as liquidity and information environment. Moreover, as mentioned earlier, most of the papers in the field do not differentiate between fundamental and spurious herding. Geographically, existing literature mainly focuses on identifying factors associated with herding in the US, developed European markets and emerging markets in Asia and the Middle East.

3. Methodology

The following section describes in detail the methodology employed by the authors of this paper to detect herding towards the market in Moscow Exchange. We employ the method proposed by Chang et al. (2000), which is centred around examining the relationship between market returns and dispersions of individual asset returns, and its modifications by Galariotis et al. (2015) and Dang & Lin (2016). In the following subsections, the authors describe the methodology in a detailed way.

3.1 Detecting herding towards the market

In order to trace herding, Chang et al. (2000) propose to use cross-sectional absolute deviation of returns (CSAD), which is defined in Equation 1:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} |R_i - R_m| \quad , \tag{1}$$

The authors show that conventional asset-pricing models predict that the relationship between CSAD and market returns should not only be positive but also linear. To do so, Chang et al. (2000) first derive the relationship between CSAD and market returns from a conventional CAPM model, which is presented in Equation 2.

$$E_t(R_i) = R_f + \beta_i E_t(R_m - R_f)\ , \tag{2}$$

where $E_i(R_t)$ is the expected return of an asset i, $E_t(R_m)$ is the expected return of an equally-weighted market portfolio, R_f is a risk-free rate of return and β_i is the measurement of the sensitivity of an asset's returns to market returns. If $\beta_m$is a systematic risk of an equally-weighted market portfolio consisting of N stocks, then:

$$\beta_m = \frac{1}{N}\sum_{i=1}^{N}\beta_i \tag{3}$$

Then, absolute value of deviation of returns (AVD) on asset i from market returns can be captured by Equation 4, while the expected cross-sectional absolute deviation of stock returns ($ECSAD$) can be measured applying Equation 5.

$$AVD_{it} = |\beta_i - \beta_m| E_t(R_m - R_f) \tag{4}$$

$$ECSAD_{it} = \frac{1}{N}\sum_{i=1}^{N} AVD_{i,t} \ = \ \frac{1}{N}\sum_{i=1}^{N}\ |\beta_i - \beta_m| E_t(R_m - R_f) \tag{5}$$

Finally, taking the first and second derivatives of $ECSAD_{it}$ the authors prove that the predicted relationship between the expected cross-sectional absolute deviation of stock returns and returns of an equally-weighted portfolio is positive and linear (Equations 6 and 7).

$$\frac{\partial ECSAD_{\ t}}{\partial E_t(R_m)} = \frac{1}{N}\sum_{i=1}^{N}\ |\beta_i - \beta_m| > 0 \tag{6}$$

$$\frac{\partial^2 ECSAD_{\ t}}{\partial E_t(R_m)^{\ 2}} = 0 \tag{7}$$

Hence, according to conventional asset-pricing models, the relationship between $ECSAD_t$ and market returns should be positive and linear. In case of a negative relationship, individual returns are clustered around market returns more than they are rationally predicted, which indicates herding. As the $ECSAD_{it}$ measure is not observed in the market, the authors proxy it by using an observable parameter of CSAD. So the main regression proposed by Chang et al. (2000), which is used in the current paper to detect herding for the overall sample of observations, is presented in Equation 8[*]:

[*] Due to a problem of autocorrelation in CSAD observations in our sample, all the tests are conducted with Newey & West (1987) HAC estimators, consistent with the literature on the issue (Chang et al., 2000; Chiang & Zheng, 2010). The Stock-Watson truncation measure for this purpose is determined as $m=0.75T^{1/3}$, where m is the number of lags and T is the number of observations in the sample (Benkovskis, 2015; and Lewis, n.d.). For our sample of observations, m = 9 lags.

$$CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + \epsilon_t \tag{8}$$

It is crucial to notice that CSAD is not a measure of herding per se, but rather it is the relationship between it and returns of an equally-weighted market portfolio that indicates the presence of herding. More precisely, herding towards the market is captured by a negative and statistically significant β_2 coefficient.

The methodology of Chang et al. (2000) has an important peculiarity that needs to be taken into account. As argued by Hachicha et al. (2010), it allows to trace herding in its most general form, not accounting for its underlying reasons. Therefore, the measure does not distinguish between fundamental and non-fundamental reasons of investors' herding. To account for this drawback, the authors of this paper employ extensions to Chang et al. (2000) methodology developed by Galariotis et al. (2015) and Dang & Lin (2016).

In their paper, Galariotis et al. (2015) propose to split variations in *CSAD* into those stemming from fundamental and non-fundamental parameters, which should allow to differentiate spurious herding from irrational one. As mentioned in the Literature Review section, spurious herding is rational, as investors do not suppress their beliefs, but rather independently take similar decisions in response to objective changes in the market. Irrational herding, as stems from the name, has non-fundamental drivers and may create distortion on the market.

To distinguish between spurious and irrational herding, Galariotis et al. (2015) propose to decompose variations in CSAD based on fundamental and non-fundamental drivers. They assume that SMB, HML and momentum factors proposed by Fama & French (1993) and Carhart (1997) provide an adequate representation of variation in CSAD due to fundamental factors. Hence, the variation in *CSAD* explained by these variables should capture spurious herding, or herding on fundamental information. On the other hand, the unexplained part represents irrational herding. The decomposition of CSAD according to Galariotis et al. (2015) is presented in Equations 9-11.

$$CSAD_t = \beta_0 + \beta_1(R_{m,t} - R_{f,t}) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t + \varepsilon_t \tag{9}$$

$$CSAD_{t,NON-FUND} = \varepsilon_t, \tag{10}$$

$$CSAD_t = CSAD_{t,FUND} + CSAD_{t,NON-FUND} \tag{11}$$

where $R_{m,t}$ is market return at time t, R_f is a risk-free rate, *HML* is a high-minus-low factor, *SMB* is a small-minus-big factor constructed according to Fama & French (1993, 1995); MOM_t is a momentum factor calculated consistent with Carhart (1997); ε_t is an error term, which in this case captures the variation in CSAD based on non-fundamental factors.

The proposed model by Galariotis et al. (2015) is further improved by Dang & Lin (2016). The authors suggest that according to the way CSAD is constructed, using absolute values of *SMB, HML* and momentum factors will give a higher explanatory power. Dang & Lin (2016) report significantly improvement in the model fit due to their modification. Hence, in this paper, the authors decompose *CSAD* into fundamental and non-fundamental parts following this methdology. The decomposition is presented in Equations 12-14.

$$CSAD_t = \beta_0 + \beta_1 |R_{m,t} - R_f| + \beta_2 |HML_t| + \beta_3 |SMB_t| + \beta_4 |MOM_t| + \varepsilon_t \tag{12}$$

$$CSAD_{t,NON-FUND} = \varepsilon_t, \tag{13}$$

$$CSAD_t = CSAD_{t,FUND} + CSAD_{t,NON-FUND} \tag{14}$$

It is important to note that there is no available dataset including *SMB, HML* and momentum factors for Russia, so the authors of this paper perform the calculations themselves. It is done consistently with Fama & French (1993) and Carhart (1997). The authors categorize the companies in the sample into small and big groups based on their market capitalization and into growth, neutral, value groups based on their book-to-market ratio. We then form six portfolios and rebalance them annually according to changes in market capitalization and book-to market ratio of portfolio constituents and consistent with Fama & French (1993). Momentum portfolios are constructed by finding high and low prior monthly aggregated returns from time period t-2 till t-12; these portfolios are rebalanced monthly. The authors also find excess market return by taking the difference between daily returns on MICEX value-weighted composite index and risk-free return, estimated with a 1-month zero-coupon bond of Russian Central Bank (RU1MT==RR).

After CSAD is decomposed, the authors run regressions specified in Equations 15 and 16 in order to detect herding towards the market due to fundamental and non-fundamental factors:

$$CSAD_{t,FUND} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + \epsilon_t \quad , \tag{15}$$

$$CSAD_{t,NON-FUND} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + \epsilon_t \quad , \tag{16}$$

Testing herding towards the market, the authors pay special attention to examining its patterns in different market states. As indicated by numerous studies (e.g. De Long, Shleifer, Summers & Waldman, 1990; Bohl & Siklos, 2008), both developed and emerging markets accommodate investors using feedback strategies. These market participants trade based on past stock returns by either buying when markets go up and selling when they decline, or doing the opposite – buying when markets plummet and selling when they soar. The existence of such trading patterns during different market states might be associated with formation of herding. The authors test this hypothesis by estimating the regression specified in Equation 17:

$$CSAD_t = \beta_0 + \beta_1 D_U|R_{m,t}| + \beta_2 D_U R_{m,t}^2 + \beta_3 D_D|R_{m,t}| + \beta_4 D_D R_{m,t}^2 \epsilon_t, \tag{17}$$

where dummy variable $D_u = 1$ if $R_{m,t} > 0$ and $D_D = 1$ if $R_{m,t} < 0$. The regression is estimated for fundamental and non-fundamental components of CSAD, which allows to understand the underlying mechanisms of herding, if it is found. Negative and statistically significant $\beta_2$or $\beta_4$coefficients would imply herding during up or down days respectively.

3.2 Testing factors associated with herding towards the market

After tracing general herding towards the market in Moscow Exchange, the authors proceed with testing specific factors potentially associated with it. For the purposes of this research, we have selected four groups of determinants: calendar effects of the Subprime crisis of 2008, Crimea annexation, Russian on-going economic turmoil, specific macroeconomic and political events; liquidity; information environment; and oil prices.

We start with testing the impact of calendar effects on herding behaviour in Moscow Exchange. As mentioned in Section 2, the empirical evidence on association between crises and herding are mixed, although most of the papers do report that herding is amplified during periods of turmoil. The authors of this paper extend the research on the impact of crises on herding to Moscow Exchange. More specifically, we test the effects of the turmoil in 2008-2009, caused by the Subprime crisis; of Crimea annexation and Russian Crisis that followed it and was caused by the US and European sanctions. To do so, for each of the aforementioned crisis periods we estimate the regression specified in Equation 18:

$$CSAD_t^C = \beta_0 + \beta_1 |R_{m,t}|^C + \beta_2 {R_{m,t}^2}^C + \epsilon_t \quad , \tag{18}$$

where $CSAD_t^C$ represents cross-sectional absolute deviation of returns during a crisis period, ${R_{m,t}}^C$and ${R_{m,t}^2}^C$ are market returns during the period of market turmoil. The regression is estimated for fundamental and non-fundamental parts of CSAD as well. A negative and statistically significant $\beta_2$coefficient would imply herding towards the market during crisis days.

Apart from testing the effects of crises, the authors also run two separate regressions to test the impact of sanctions announcements and important macroeconomic news releases on herding. As obtaining Newey & West (1987) HAC estimators requires all the regression variables to be regularly distributed (which is not the case with dummies for announcement days), the authors cannot test the effects of sanctions announcements and macroeconomic news releases in the same way we test the effects of crises. To account for this, the authors alter the regression preserving the rationale behind it. The regressions are specified in Equations 19-20:

$$CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + \beta_3 D_S R_{m,t}^2 \epsilon_t \tag{19}$$

$$CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + \beta_3 D_M R_{m,t}^2 \epsilon_t \tag{20}$$

where dummy variable $D_S = 1$ for days of sanctions announcements, and 0 otherwise $D_M = 1$ for days of important macroeconomic announcements, and 0 otherwise. Types of macroeconomic announcements included into the analysis are discussed in subsection 3.3. A negative and statistically significant β_3 coefficient in each regression would imply herding towards the market during announcement days.

After testing calendar effects, the authors proceed with tests on information environment. As mentioned in Section 2, size of the company might positively correlate with how easy it is for investors to obtain information about it (Thirikwa, 2015; Özsu, 2015). Hence, the authors choose market capitalization as the first proxy of information enfironment and test its association with herding. To do so, the authors split the companies in the initial sample into quartiles according to their size; thus, obtaining four portfolios. We then estimate regression in Equation 21 for all of the portfolios according to the following example:

$$CSAD_{1.port.,t} = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + \epsilon_t \tag{21}$$

where $CSAD_{1.port.,t}$ is a cross-sectional absolute deviation of returns of portfolio one, $R_{m,t}$ and $R^2_{m,t}$ represent returns on an equally-weighted market portfolio. The authors also run regression 21 for fundamental and non-fundamental components of CSAD. A negative and statistically significant β_2 coefficient would imply herding towards the market within a given portfolio.

As mentioned in Section 2, herd behaviour might be caused by the lack of investors' confidence in their abilities and reputational concerns (Bikchandani & Sharma, 2001). When this is the case, some of the market participants might follow the advice of professional financial analysts and, in doing so, herd around them. In their discussion paper, Chong et al. (2016) suggest that when the number of analysts following a particular company is large, the information environment of this company improves. Hence, the authors use the number of analysts following a particular company as another proxy for information environment. The authors split the initial sample of companies into four quartiles according to the average number of analysts following them and obtain four portfolios. We then run regression specified in Equation 21 on all four portfolios and for both fundamental and non-fundamental CSAD components. A negative and statistically significant β_2 coefficient would imply herding towards the market within a given portfolio.

Moving on, the authors test the association between liquidity and market-wide herding. As liquidity is a relatively elusive phenomenon which has different dimensions, the authors use two liquidity measures, capturing different aspects of it. First of all, the authors construct a liquidity measure based on daily trading volumes. We create a dummy variable for high-liquidity days, which is equal to one for the days when trading volume was above its 75th percentile; and a dummy for low-liquidity days, which is equal to one for the days with trading volume lower than the 25th percentile. We then run the regression specified in Equation 22 for total CSAD and both its fundamental and non-fundamental components:

$$CSAD_t = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R^2_{m,t} + \beta_3 D_L R^2_{m,t} + \beta_4 D_H R^2_{m,t} + \epsilon_t \qquad (22)$$

where dummy variable $D_L = 1$ if trading volume lies in the lowest 25%, and 0 otherwise, and $D_H = 1$ if trading volume lies in the highest 25%, and 0 otherwise. Negative and statistically significant β_3 or β_4 coefficients would imply herding during low or high liquidity days respectively.

Apart from a trading volume proxy, the authors also use Amihud (2002) illiquidity measure, which is regarded as a reliable illiquidity measure in relevant literature (e.g. Gayenko et al., 2009; Galariotis et al. 2015). It is calculated according to Equation 23:

$$Illiq_{i,t} = \frac{1}{N} \sum_{t=1}^{N} \left(\frac{|R_{i,t}|}{P_{i,t} VO_{i,t}} \right) \qquad (23)$$

where $R_{i,t}$ is stock's returns at time t, $P_{i,t}$ is price and $VO_{i,t}$ is volume traded of stock *i* at time t. The measure shows the monetary amount of a stock that needs to be traded in order to move the price of a stock away from its current value. Hence, when the measure is high, the market's liquidity is low, as the price of a stock will react significantly to a relatively small monetary amount of trades. On the other hand, when the measure is low, the market is liquid. To incorporate the measure into the analysis, the authors construct a dummy variable for high-liquidity days, which is equal to one for the days when Amihud measure is in its lowest 25th percentile; and a dummy for low-liquidity days, for the days when Amihud measure is in its highest 25th percentile. We then run the regressions specified in Equation 24 for total CSAD and both its fundamental and non-fundamental components:

$$CSAD_t = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R^2_{m,t} + \beta_3 D_L R^2_{m,t} + \beta_4 D_H R^2_{m,t} + \epsilon_t \qquad (24)$$

where dummy variable $D_L = 1$, when Amihud measure is in the lowest 25th percentile, and 0 otherwise, and $D_H = 1$ when Amihud measure is in the highest 25th percentile, and 0 otherwise. Negative and statistically significant β_3 or β_4 coefficients would imply herding during low or high liquidity days respectively.

Finally, the authors test the association between oil price movements and market-wide herding in Moscow Exchange. Russia is one of the world's leading oil exporters, which is very much reflected in its financial market: oil & gas corporations account for 32.6% of total market capitalization (Appendix B). Hence, fluctuations in oil prices should have a pronounced impact on Russian financial market and, potentially, on herding. To test this relationship, the authors run the following regression:

$$CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + \beta_3 D_{U,5\%} R_{m,t}^2 + \beta_4 D_{D,5\%} R_{m,t}^2 + \epsilon_t, \tag{25}$$

where $D_{U,5\%}$is a dummy equal to one on the days when the change in oil price lies in extreme upper 5%,, and 0 otherwise. $D_{l,5\%}$ equals to one on the days when the change in oil price lies in extreme lower 5%, and 0 otherwise. As a robustness check, we also test a 1% threshold for extreme oil price movements. Negative and statistically significant $\beta_3$or $\beta_4$coefficients would imply herding during days of extreme up or down oil price movements respectively.

3.3 Data description

For purposes of the current research, the authors extract daily data on individually adjusted stock prices, market capitalization, book-to-market ratio, trading volumes, number of shares outstanding and number of analysts tracking a particular company from Thomson Reuters Datastream for all the stocks traded at Moscow Exchange. The authors also extract closing Brent crude oil prices from the same database. We then adjust our sample based on data criteria, excluding companies missing substantial amount of information on closing prices, market capitalization, number of shares outstanding, etc. As Thomson Reuters Datastream reports dates of national holidays when no trading takes place as zeros, the authors manually exclude these observations. Having done so, we obtain the dataset of 1842 daily observations including 120 companies, which constitute 85.7% of the total market capitalization of Moscow Exchange (Appendix B).

Using this dataset, the authors create an equally-weighted market portfolio and rebalance it to account for changes in portfolio composition. We then calculate CSAD for the whole sample, as specified in Equation 1. This allows to set up the basis of the model for testing herd behaviour in Moscow Exchange. The authors then divide companies in the sample into quartiles based on the following criteria: number of analysts following a company and market capitalization. Thus, we additionally obtain two sets of portfolios, for which we calculate CSAD.

Descriptive statistics of these variables are presented in Table 1. As seen in the table, the final sample includes 1842 daily return and CSAD observations. Mean returns on an equally-weighted market portfolio are equal to 0.00% and their standard deviation is 2.22%.

Variable		Observations	Mean	Std. Dev.	Min	Max	ADF
All days							
Full sample	Rm	1842	0.00%	1.43%	-12.27%	7.65%	-37.060***
	CSAD	1842	1.89%	1.02%	0.16%	9.19%	-15.065***
Portfolios by # of analysts following							
Portfolio 1 (least analysts)	CSAD	1842	2.28%	1.33%	0.08%	15.69%	-20.886***
Portfolio 2	CSAD	1842	1.97%	1.36%	0.08%	18.45%	-20.714***
Portfolio 3	CSAD	1842	1.81%	1.12%	0.08%	13.78%	-16.983***
Portfolio 4 (most analysts)	CSAD	1842	1.56%	1.01%	0.41%	18.04%	-17.607***
Portfolios by market capitalization							
Portfolio 1 (smallest)	CSAD	1842	2.26%	1.41%	0.08%	20.98%	-21.363***
Portfolio 2	CSAD	1842	2.02%	1.27%	0.08%	16.75%	-19.526***
Portfolio 3	CSAD	1842	1.78%	1.14%	0.08%	19.78%	-17.629***
Portfolio 4 (largest)	CSAD	1842	1.51%	1.01%	0.38%	13.68%	-18.468***

Table 1. Descriptive statistics of returns on equally-weighted portfolios and CSAD (Made by the authors)
***- significant at 1% significance level

The lower bound of CSAD is limited to 0 by construction, as only absolute values are used for its calculation; when market returns increase, CSAD does so as well. Descriptive statistics on portfolio returns are presented in Table 1. We also report the results of augmented Dickey-Fuller test for all the variables. As seen from the results of the test reported in the ADF column, equally-weighted returns and CSAD for all of the formed portfolios are stationary.

The data about important macroeconomic news releases are manually collected from Financial Times Economic Calendar (Financial Times, 2017). The data include important international and domestic announcements. For international events, we document dates of important international meetings and forums, releases of country reports and forecasts, as well as industry report releases. For Russia-specific events, we look at the dates of key interest rate announcements by the Central Bank of Russian Federation, announcements of real wages dynamics, unemployment, trade balance and inflation (Appendix C).

The sample period examined in the study is 2008-2015, starting on 01/04/2008 and ending on 30/12/2015. Observations for 2016 are excluded due to data availability reasons, as there is lack of reliable data on book-to-market ratio, which is utilized to obtain SMB, HML and momentum factors. The timespan of the dataset enables us to examine herding in the context of three important macroeconomic and geopolitical events: two recent crises that affected Russian economy – Subprime crisis of 2008, current Russian crisis started in 2014 – and the days of Crimea annexation, which caused that turmoil in 2014 and provoked sanctions implementation.

The authors define the most severe period of subprime crisis in Russia to take place during the period of 12/05/2008-30/12/2008. As seen in Figure 1, this period incorporates the days, when MICEX Index, a value-weighted composite index calculated based on prices of 50 most liquid Russian stocks, fell cumulatively by more than 50%. The period includes the most turbulent days for Russian stock market: June 24th, when Russian then-prime-minister Vladimir Putin criticized top management of Mechel company, which caused the first abrupt fall of the market; the period of Russian-Georgian military conflict in August 2008 and the week of November 10-14th, when Russian stock market showed the worst decline among all world's financial markets. In January 2009, the financial market stabilized and started to recover.

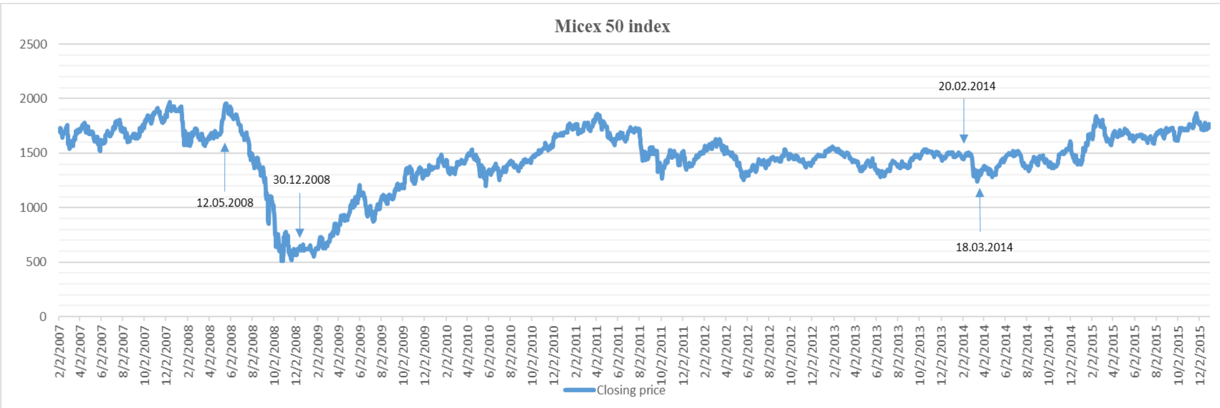

Figure 1. Dynamics of MICEX index, a value-weighted composite index calculated based comprised of the 50 most liquid Russian stocks. Made by the authors using data from Thomson Reuters Datastream.

The period of Crimea annexation is defined to start on the 20th of February 2014, when Ukraine for the first time openly reported aggression against it from the Russian side, which caused first shocks on the Russian stock market. The period ends on the 18th of March 2014, when the Russian State Government signed a treaty of Crimea's adoption (BBC, 2015). During this time, Moscow stock market plummeted by 10,8% (Figure 1). The time after the annexation and until the ending date of the sample is regarded as Russian crisis, which was enhanced by sanctions and may be generally surrounded by more uncertainty than regular days.

4. Empirical results

This section presents the results of empirical tests of herding in Moscow Exchange. The authors first report the results of market-wide herding tests on an overall sample and proceed with reporting the results of tests for factors associated with herding. All the tests are run in accordance with Newey & West (1987) heteroscedasticity and autocorrelation consistent estimators.

4.1 Overall market-wide herding

The authors start examining herding towards the market in Moscow Exchange by estimating the regression specified in Equation 8 for the whole sample. As seen in Table 2, we find evidence of irrational market-wide herding in Moscow Exchange during the period of 01/04/2008–30/12/2015, which is captured by a negative and statistically significant coefficient before $R^2_{m,t}$ in regression with $CSAD_{NON\text{-}FUND}$ as a dependent variable. We do not find any evidence of spurious herding for the full sample of observations, which is portrayed by a non-negative coefficient before $R^2_{m,t}$ in regression with $CSAD_{FUND}$ as a dependent variable.

The authors further test herding in up and down markets; the results are also presented in Table 2. We find irrational herding to be prevalent during days with negative market returns, which is captured by a negative and statistically significant coefficient before $R^2_{m,t}$ in regression with $CSAD_{NON\text{-}FUND}$ as a dependent variable. The authors do not find any evidence of spurious herding in both up and down markets.

	Full sample				Up market			Down market		
	Intercept	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	adj. R^2	*Intercept*	$D_U\lvert R_{m,t}\rvert$	$D_U R^2_{m,t}$	$D_D\lvert R_{m,t}\rvert$	$D_D R^2_{m,t}$	adj. R^2
Total herding (CSAD)	0.0129	0.6395	0.3331	0.496	0.0134	0.4878	6.9204	-0.5816	-0.0901	0.518
p-value	*0.000****	*0.000****	*0.765*		*0.000****	*0.000****	*0.000****	*0.000****	*0.918*	
Spurious ($CSAD_{FUND}$)	0.0145	0.4420	1.5212	0.581	0.0149	0.3157	6.7214	0.4040	1.1193	0.604
p-value	*0.000****	*0.000****	*0.062***		*0.000****	*0.000****	*0.000****	*0.000****	*0.789*	
Irrational ($CSAD_{NON\text{-}FUND}$)	-0.0015	0.1976	**-1.1881**	0.048	-0.0015	0.1721	0.1991	0.1776	**-1.2095**	0.05
p-value	*0.000****	*0.000****	***0.052*****		*0.000****	*0.009****	*0.916*	*0.004****	***0.053*****	

Table 2. Results of overall herding tests (using Equation 8) and tests for spurious and fundamental herding for up and down market states (Equation 17). Made by the authors. * - significant at 10% significance level, ** - significant at 5% significance level, *** - significant at 1% significance level.

4.2 Herding and calendar effects

As mentioned in previous sections, to research the association between specific calendar effects and market-wide herding in Moscow Exchange, the authors select three important macroeconomic and geopolitical events that took place during the period of 2008-2015: Subprime crisis of 2008, annexation of Crimea and Russian crisis of 2014-2015. Apart from that, we also test for the association between herding and important macroeconomic and sanctions announcements that happened within the review period. The results of the tests are reported in Table 3.

Herding during market turmoil periods is traced according to the regression specified in Equation 18 for aggregate CSAD and its fundamentals- and non-fundamentals-driven components. The authors find evidence of herding behaviour, represented by negative and statistically significant coefficient before $R^2_{m,t}$, during Subprime crisis and Crimea annexation. As seen in Table 3, Panel A, the authors do not find any statistically significant evidence of overall, fundamental and non-fundamental herding during Russian crisis. While no spurious herding is revealed during these crisis periods, it is peculiar that the coefficient before $R^2_{m,t}$ for $CSAD_{FUND}$ regression during Crimea annexation and Russian crisis is negative. This might suggest that in certain moments during the review period, there might have been traces of spurious herding.

Total herding (CSAD)										
Panel A	*Intercept*	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	adj. R^2	*Panel B*	*Intercept*	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$DR^2_{m,t}$	adj. R^2
Subprime crisis	0.0187	0.9469	**-3.0565**	0.546	Sanctions	0.0129	0.6343	0.3699	7.3222	0.498
p-value	0.000***	0.000***	0.037**		*p-value*	0.000***	0.000***	0.739	0.131	
Crimea annexation	0.0128	0.601	**-2.231**	0.879						
p-value	0.000***	0.000***	0.008***		Macronews	0.0131	0.6055	1.5793	**-4.7007**	0.509
Russian crisis	0.0155	0.1347	22.7955	0.509	*p-value*	0.000***	0.000***	0.282	0.000***	
p-value	0.000***	0.138	0.000***							
Spurious herding ($CSAD_{FUND}$)										
Subprime crisis	0.0167	0.5656	0.4866	0.604	Sanctions	0.0145	0.4444	1.5044	**-3.3468**	0.581
p-value	0.000***	0.000***	0.627		*p-value*	0.000***	0.000***	0.066*	0.001***	
Crimea annexation	0.0136	0.3874	-0.2011	0.923						
p-value	0.000***	0.000***	0.646		Macronews	0.0146	0.4184	2.3855	**-3.2601**	0.593
Russian crisis	0.0151	0.3782	-1.4763	0.216	*p-value*	0.000***	0.000***	0.009***	0.000***	
p-value	0.000***	0.000***	0.473							
Irrational herding ($CSAD_{NON\text{-}FUND}$)										
Subprime crisis	0.0019	0.3813	**-3.5431**	0.052	Sanctions	-0.0015	0.1899	-1.135	10.669	0.054
p-value	0.43	0.001***	0.001***		*p-value*	0.000***	0.000***	0.060**	0.015**	
Crimea annexation	-0.0008	0.2136	**-2.03**	0.107						
p-value	0.613	0.011**	0.004***		Macronews	-0.0015	0.1871	-0.806	**-1.4406**	0.05
Russian crisis	0.0003	-0.2435	24.2718	0.245	*p-value*	0.000***	0.001***	0.308	0.038**	
p-value	0.377	0.002***	0.000***							

Table 3. Results of herding tests during market turmoil periods based on Equation 18 (Panel A) and during days of sanctions and macroeconomic news announcements based on Equations 19 and 20 (Panel B). Made by the authors. * -significant at 10% significance level, ** - significant at 5% significance level, *** - significant at 1% significance level.

Having carried out tests on market turmoil periods, the authors proceed with the analysis of different macroeconomic news announcements. The results of the tests are presented in Table 3, Panel B. Herding during sanctions announcements and macroeconomic news release days is traced with the use of regressions specified in Equations 19 and 20. The authors find statistically significant evidence of total, spurious and irrational herding during the days of important macroeconomic news releases (e.g. key interest rate, unemployment rate, real wage growth announcements). This is captured by a negative and statistically significant coefficient before $R^2_{m,t}$ for all three regressions. Furthermore, authors also find evidence of herding towards fundamentals represented by negative and statistically significant coefficient before $R^2_{m,t}$ for the days of sanctions announcements, while overall herding and non-fundamental herding towards the market does not prevail during these days.

4.3 Herding and information environment

To test the relationship between herding and information environment, the authors conduct a series of tests on portfolios split by the number of financial analysts following a company and market capitalization. The authors first look at how the presence of financial specialists analysing a company's performance affects herding. To do so, we run regressions specified in Equation 21 for all four portfolios. Results of the tests are presented in Table 4. The existence of market-wide herding is again captured by a negative and statistically significant coefficient before $R^2_{m,t}$. Similar to findings of the overall regression, the authors find no evidence of overall herding in any of the portfolios. Moreover, no indication of herding on fundamental information is present in any of the portfolios. At the same time, the authors do find traces of irrational herding that prevails in stocks with relatively smaller number of analysts in portfolio two. It is notable that coefficients capturing irrational herding are negative for all four portfolios, but only the coefficient for portfolio two is statistically significant.

Portfolios by # of analysts following	Total herding (CSAD)				Spurious herding ($CSAD_{FUND}$)				Irrational herding ($CSAD_{NON\text{-}FUND}$)			
	Intercept	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	Adj. R^2	*Intercept*	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	Adj. R^2	*Intercept*	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	Adj. R^2
Portfolio 1 (least analysts)	0.0168	0.6296	1.0969	0.318	0.0185	0.4404	1.5646	0.634	-0.0016	0.1893	-0.4667	0.025
p-value	*0.000****	*0.000****	*0.475*		*0.000****	*0.000****	*0.029**		*0.001****	*0.023***	*0.743*	
Portfolio 2	0.0124	0.7951	-0.3884	0.385	0.0148	0.4834	2.0184	0.514	-0.0024	0.3117	**-2.4068**	0.044
p-value	*0.000****	*0.000****	*0.847*		*0.000****	*0.000****	*0.092**		*0.000****	*0.000****	***0.03*****	
Portfolio 3	0.0126	0.5966	0.2594	0.356	0.0139	0.4230	1.2391	0.567	-0.0014	0.1736	-0.9798	0.024
p-value	*0.000****	*0.000****	*0.823*		*0.000****	*0.000****	*0.085**		*0.000****	*0.002****	*0.197*	
Portfolio 4 (most analysts)	0.0107	0.5202	0.5163	0.349	0.0116	0.4114	1.2093	0.583	-0.0009	0.1088	-0.6930	0.012
p-value	*0.000****	*0.000****	*0.064*		*0.000****	*0.000****	*0.073**		*0.007****	*0.057***	*0.471*	

Table 4. Results of herding tests on portfolios formed by number of analysts tracking a company as specified in Equation 21 (Made by the authors). * - significance at 10% significance level, ** - significance at 5% significance level, *** - significance at 1% significance level.

Having analysed herding in portfolios split by the number of analysts tracking a particular company, the authors conduct herding tests on four portfolios formed according to market capitalization by estimating the regression specified in Equation 21. The results of the tests are reported in Table 5. The existence of market-wide herding is captured by a negative and statistically significant coefficient before $R^2_{m,t}$.

Portfolios by Mcap	Total herding (CSAD)				Spurious herding ($CSAD_{FUND}$)				Irrational herding ($CSAD_{NON-FUND}$)			
	Intercept	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	Adj. R^2	*Intercept*	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	Adj. R^2	*Intercept*	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	Adj. R^2
Portfolio 1 (lowest)	0.0157	0.7204	1.0340	0.362	0.0178	0.4788	2.0045	0.536	-0.0020	0.2417	-0.9705	0.035
p-value	*0.000****	*0.000****	*0.594*		*0.000****	*0.000****	*0.08**		*0.000****	*0.000***	*0.340*	
Portfolio 2	0.0136	0.7515	-1.0089	0.362	0.0158	0.4454	1.5485	0.565	-0.0022	0.3061	**-2.5574**	0.04
p-value	*0.000****	*0.000****	*0.355*		*0.000****	*0.000****	*0.069**		*0.000****	*0.000****	***0.002*****	
Portfolio 3	0.0126	0.5626	0.3260	0.309	0.0140	0.3871	1.2282	0.580	-0.0014	0.1755	-0.9022	0.022
p-value	*0.000****	*0.000****	*0.727*		*0.000****	*0.000****	*0.066**		*0.000****	*0.003****	*0.310*	
Portfolio 4 (highest)	0.0102	0.5087	1.1166	0.379	0.0107	0.4490	1.2778	0.599	-0.0005	0.0597	-0.1613	0.006
p-value	*0.000****	*0.000****	*0.403*		*0.000****	*0.000****	*0.066**		*0.114*	*0.295*	*0.845*	

Table 5. Results of herding tests on portfolios formed by market capitalization, as specified in Equation 21. (Made by the authors). * - significance at 10% significance level, ** - significance at 5% significance level, *** - significance at 1% significance level.

No statistically significant evidence of herding towards the market is observed for total and spurious herding; however, irrational herding is present for portfolio 2 which represents relatively small stocks compared to market average over the period of 2008-2015. These results are similar to the ones for portfolios formed on number of analysts following a company, although their compositions are 67% different.

4.4 Herding and liquidity

The association between market-wide herding and liquidity is tested by two different measures: Amihud illiquidity and trading volume. For this purpose, the authors estimate regressions according to Equations 22 and 24 for total CSAD, fundamentals- and non-fundamentals-driven herding. The results of the tests are presented in Table 6.

The authors find negative and statistically significant coefficient before $R^2_{m,t}$ on overall herding towards the market in high-liquidity days measured by Amihud illiquidity measure, however, using volume measure no confirmation of overall herding is found. Furthermore, both liquidity measures show strong evidence of spurious herding in high-liquidity days. The results of empirical tests indicate no evidence of herding during low-liquidity days. Additionally, there is no statistically significant indication of irrational herding presence during high- and low-liquidity days.

Liquidity	Amihud measure						Volume measure					
	Intercept	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$D_L R^2_{m,t}$	$D_H R^2_{m,t}$	adj. R^2	*Intercept*	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$D_L R^2_{m,t}$	$D_H R^2_{m,t}$	adj. R^2
Total herding (CSAD)	0.0127	0.7126	-1.0874	1.1182	**-7.8767**	0.515	0.0131	0.6049	-0.073	4.7573	0.6758	0.509
p-value	*0.000****	*0.000****	*0.564*	*0.458*	***0.000*****		*0.000****	*0.000****	*0.930*	*0.000****	0.622	
Spurious ($CSAD_{FUND}$)	0.0145	0.4534	2.3293	-0.9771	**-5.2418**	0.592	0.0144	0.4705	1.2829	2.1359	**-2.3237**	0.597
p-value	*0.000****	*0.000****	*0.181*	*0.506*	**0.000*****		*0.000****	*0.000****	*0.094**	*0.233*	***0.011****	
Irrational ($CSAD_{NON-FU}$	-0.0017	0.2592	-3.4168	2.0953	-2.6351	0.063	-0.0012	0.1345	-1.356	2.6215	2.995	0.064
p-value	*0.000****	*0.000****	0.001***	0.012**	0.134		*0.000****	*0.003****	*).004****	*0.167*	*0.011***	

Table 6. Results of tests on an association between herding and liquidity based on Equations 22 and 24. (Made by the authors) * - significance at 10% significance level, ** - significance at 5% significance level, *** - significance at 1% significance level.

4.5 Herding and oil price fluctuations

Examining the relationship between extreme oil price movements and market-wide herding, the authors run the regression specified in Equation 25. The results of the tests are presented in Table 7. While no negative and significant relationship is found in overall and fundamental market wide herding, we do find irrational herding patterns in case of extreme upward oil price movements for both 5% and 1% thresholds. We do not find evidence of irrational herding during the days of extreme downward oil price movements.

	Intercept	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$D_U R^2_{m,t}$	$D_D R^2_{m,t}$	adj. R^2
Total herding (CSAD)						
Extreme 1% movement	0.0131	0.6267	-0.0291	6.7554	2.441	0.5053
p-value	*0.000****	*0.000****	*0.976*	*0.001****	*0.031***	
Extreme 5% movement	0.0129	0.6522	-1.0847	4.3587	1.4927	0.5041
p-value	*0.000****	*0.000****	*0.407*	*0.000****	*0.212*	
Spurious herding ($CSAD_{FUND}$)						
Extreme 1% movement	0.0146	0.4243	1.3418	10.9057	0.5234	0.6135
p-value	*0.000****	*0.000****	*0.079**	*0.000****	*0.676*	
Extreme 5% movement	0.0145	0.4627	-0.8921	7.5563	2.5346	0.6254
p-value	*0.000****	*0.000****	*0.378*	*0.000****	*0.087**	
Irrational herding ($CSAD_{NON-FUND}$)						
Extreme 1% movement	-0.0016	0.2025	-1.3709	**-4.1503**	1.9171	0.0577
p-value	*0.000****	*0.000****	*0.022*	***0.047*****	*0.128*	
Extreme 5% movement	-0.0016	0.1896	-0.1927	**-3.1976**	-1.0418	0.0565
p-value	*0.000****	*0.000****	*0.896*	***0.071****	*0.412*	

Table 7. Results of herding tests on extreme upward and downward daily oil price movements based on Equation 25. (Made by the authors). * - significant at 10% significance level, ** - significant at 5% significance level, *** - significant at 1% significance level.

4.6 Summary of results

The summary of the results obtained from all regressions in our analysis is presented in Table 8. As it may be observed, the authors find irrational herding during down days, Subprime Crisis, Crimea annexation, days of macroeconomic news releases. Spurious herding is found during the days of high liquidity, macroeconomic news releases and sanctions announcements. The authors do not find a compelling evidence of significant association between herding and information environment proxied by the number of analysts following a company and a company's size. Yet, our empirical findings suggest that small stocks with fewer analysts might be more prone to herding behaviour. Additionally, extreme positive oil price movements are linked to non-fundamental herding behaviour while negative extreme movements do not provide any manifestation of it.

	Total herding (CSAD)	Spurious herding ($CSAD_{FUND}$)	Irrational herding ($CSAD_{NON\text{-}FUND}$)
Overall	No	No	Yes
Up-days	No	No	No
Down-days	No	No	Yes
Subprime crisis	Yes	No	Yes
Crimea annexation	Yes	No	Yes
Russian crisis	No	No	No
Sanctions announcements	No	Yes	No
Macroeconomic announcements	Yes	Yes	Yes
Companies with least analysts	No	No	Yes (portfolio 2)
Companies with most analysts	No	No	No
Smaller companies	No	No	Yes (portfolio 2)
Larger companies	No	No	No
Low liquidity (Amihud measure)	No	No	No
High liquidity (Amihud measure)	Yes	Yes	No
Low liquidity (Volume measure)	No	No	No
High liquidity (Volume measure)	No	Yes	No
Oil price extreme up	No	No	Yes
Oil price extreme down	No	No	No

Table 8. Summary of empirical results. (Made by the authors)

5. Discussion of results

5.1. Results of market-wide herding tests

The results of the tests on the full sample of selected stocks traded on Moscow Exchange over the period of 01/04/2008 - 30/12/2015 indicate that Russian stock market exhibits signs of irrational market-wide herding over the whole sample period. These findings are consistent with those for less developed markets, like South Korea and Taiwan (Chang et al., 2000), and are contrary to findings for the developed markets of the US and the UK (Galariotis et al. 2015). This evidence suggests that Russian stock market does not yet belong in the same group with the world's largest and most profound financial markets, like the US and the UK, where herding is not an omnipresent, but rather a periodic phenomenon. At the same time, one might conclude that Russian market shows herding patterns similar to developed European financial markets, like France and Germany, as reported by Chiang & Zheng (2010).

According to the results obtained, overall irrational herding in Russian stock market is propelled by investors' mimicking each other in down-days. One potential explanation is that the results of our tests in down-days are significantly impacted by crisis periods when the market fell substantially. These are the periods of highest uncertainty, so investors try to infer some information about future by following the market (Christie & Huang, 1995). Another potential explanation of this phenomenon might be found in the arguments of Shefrin &

Statman (1985), who describe that an average investor is much more reluctant to realize losses than to realize gains (a phenomenon called "disposition effect"). In line with this argument, when the market is down a significant number of investors might prefer to hold on to their assets even despite objective information, and in doing so, herd. Finally, the empirical evidence we have collected is generally consistent with the findings of McQueen, Pinegar & Thorley (1996), who mention that small stocks usually react slowly to good news. The authors of this paper use an equally-weighted market portfolio, which is more affected by small capitalization stocks. Hence this phenomenon of underreaction will mean lower returns dispersion in up-markets, which may explain our findings.

5.2. Results of tests on factors associated with herding

Testing the association between specific calendar events and herding, the authors of this paper conclude that herding in Russian stock market is significantly associated with the periods of high uncertainty and turmoil. Our findings with this respect are consistent with the general line of thought in academic literature on the issue formulated by Christie & Huang (1995) and Chang et al. (2000). Among the three major geopolitical events – Subprime Crisis of 2008, Crimea Annexation in February/March 2014, and Russian Crisis that followed – we document a strong evidence of market-wide herding during both Subprime Crisis and Crimea annexation. We do not find a statistically significant evidence of market-wide herding during the Russian Crisis of 2014-2015.

Our analysis of the periods of Subprime Crisis of 2008 and Crimea annexation suggests that market-wide herding observed during this time is irrational in its nature and driven by non-fundamental factors. This again supports the idea of herding being triggered by surges in uncertainty on the market, which was exactly the case with the two aforementioned events. Being completely unexpected and having significant potential political and economic repercussions, Subprime crisis and Crimea annexation indeed provoked a huge spike in uncertainty. In such environment lacking sources of reliable information, investors in MICEX-traded companies tried to infer it from the market, and, in doing so, opted for herding. The empirical evidence suggests that, for instance, as Crimea annexation unfolded, investors indeed took active steps and went as far as to retreat from Russian equity funds (Flood, 2014). Our empirical results with this respect are consistent with the evidence for the US market reported by Galariotis et al. (2015).

The authors find no significant association between herding towards the market and Russian crisis of 2014-2015, which followed the annexation of Crimea. One explanation for this phenomenon might lie in lower levels of uncertainty on the market during this period of time. While the Subprime Crisis and Crimea annexation unfolded instantaneously, Russian Crisis could have been foreseen by investors from the world's reaction to Crimea annexation. Hence, one can argue that after Crimea became a part of Russian Federation the level of uncertainty surrounding the country gradually declined. The empirical evidence supports this argument – we do not find statistically significant irrational herding during this period. It is notable, however, that the coefficient capturing spurious herding during this period does turn negative but remains insignificant.

The negative but statistically insignificant spurious herding indicator for the days of the Russian Crisis 2014-2015 suggests that there might be potential fundamentally-driven herding during some days within this timespan. We hypothesise that spurious herding might occur in days of sanction announcements, as the introduction of sanctions means changes in fundamental information both on the aggregate market level and for specific companies (some sanctions are targeted specifically at shareholders and top managers of big Russian corporations). As reported in Section 5, we do find statistically significant evidence of spurious herding during the days when sanctions were announced. As sanctions are announced publically, all investors have access to the information and it is natural that many of them analyse it in a similar way and make similar investment decisions. Hence, the evidence of spurious herding during the days of sanctions announcements is in compliance with the theoretical background.

Apart from analysing herding during the days of sanctions announcements, the authors also look at the days, when some important macroeconomic news were revealed (e.g. GDP growth, CPI, unemployment rates, key interest rate, etc.). Similar to sanctions, macroeconomic news releases impact investors' views of the future state of Russian economy and financial market. Hence, consistent with the results for sanctions announcement days, we find spurious herding during the days of macroeconomic news releases as well. The findings of spurious herding during the days of sanctions announcements and macroeconomic news releases are logical. At the same time, it is peculiar that we also find significant irrational market-wide herding during these days. One of the reasons that could explain such pattern might be unsophisticated investors. Being aware of potential repercussions of macroeconomic news, these investors might be willing to speculate on them. Yet, lacking enough knowledge or skill to analyze the information, they try to infer it from the market and possibly from other unsophisticated investors. These actions might bias market behaviour and lead to a formation of irrational herds among investors.

The authors of this paper have not been able to find a very robust association between information environment and market-wide herding. At the same time, the analysis of our results suggests that herding is more likely to be witnessed among smaller companies and companies with less analysts following. While we do not observe any type of market-wide herding in two portfolios with largest companies and in two portfolios with the most analysts following, the situation is different for portfolios with smaller companies and fewer analysts following. More precisely, we find statistically significant evidence of irrational herding in the second-quartile portfolios in both samples. Interestingly, we do not find any herding patterns in portfolios consisting of smallest stocks and stocks with least analysts. A potential explanation for such findings might be the fact that investors are mostly uninterested in stock constituting the lowest portfolios, as there is too little market information about them on the market. Trades with this stocks are mostly carried out by rational investors, who possess adequate knowledge of the market or have some private information about these stocks. At the same time, companies in second portfolios are larger, receive wider attention from the public, and are hence more prone to irrational investors' behaviour. As there is still relatively little information on the market about these companies, less sophisticated investors might find it difficult to trade purely by themselves and, hence, opt for mimicking others. For larger stocks and equities with more analysts following, the problem of asymmetric information appears to be less pronounced, as we do not find any significant evidence of herding. Moreover, the coefficients capturing herding become more insignificant and lower in absolute terms from portfolio 2 to portfolio 4.

Testing the association between liquidity and market-wide herding, we find a statistically significant evidence of spurious herding during high-liquidity days. The results are robust with respect to two alternative liquidity measures. These results are consistent with Galariotis et al. (2016), who also find evidence of herding during high-liquidity days. Yet, in our paper, we expand on the research of Galariotis et al. (2016) by estimating that herding in high-liquidity days in Moscow Exchange is driven by fundamental factors and, hence, should not lead to asset mispricing. Given the methodological design of this research, the authors are unable to identify quantitatively whether herding is caused by high liquidity on the market, or the relationship is the opposite. However, since it is revealed that herding during high-liquidity days is driven by fundamental factors, the authors propose that spurious herding might naturally cause high liquidity. When a new piece of information is released, investors adjust their positions accordingly and practically simultaneously, which is believed to cause higher-than-average liquidity on the market.

Finally, testing the association between extreme oil price movements and herding, the authors report evidence of non-fundamental herding during extreme up-movements, which holds both for 5% and 1% threshold. One explanation of this phenomenon may be found in behaviour of unsophisticated investors. Seeing significant positive daily price movements, these investors might misinterpret this signal (as described by DeLong et al., 1990), consider it as an indication of further price growth and, hence, step in to reap the profit. Another potential explanation may be the presence of positive feedback traders, who take similar positions when oil prices increase substantially. It is peculiar, that we do not find a statistically significant evidence of herding during days of extreme negative oil price movements. One potential explanation for this phenomenon might lie in the fact that Russian oil companies, while being public, are largely controlled and supported by the country's government. Hence, oil price shocks do not cause that much distortion for them. What is more, according to Fadeeva (2015), Russian oil companies suffered relatively little as a result of recent oil price drops, because their revenues are denominated mostly in US dollars, while costs are in Russian rubles (which devalued significantly following Crimea annexation). The evidence of no herding during extreme downward oil price fluctuations suggests that the market is aware of this pecularity.

5.3 Contribution of the study

To conclude the section, the results obtained by the authors add up to existing body of empirical research on herding in a number of ways. First of all, the authors empirically show the importance of distinguishing between spurious and irrational herding. As a matter of fact, this issue is not adequately addressed in most of the papers studying herding in financial markets (among others, Gavrilidis et al., 2015; Chong et al., 2016), which could lead to obtaining biased results. For instance, in the case of Russian stock market, not separating herding according to different drivers would result in reporting no herding behaviour on a regular basis. However, decomposing herding into spurious and irrational one, we find the latter component to be statistically significant.Apart from enabling researchers to obtain more robust and complete results, distinguishing spurious from irrational herding should prove useful and more informative than overall herding tests for people making investment decisions. It is crucial to understand that spurious herding does not lead to asset mispricing and is an efficient way of market reaction to a new piece of information.

Secondly, the authors expand the evidence on association between herding and a number of factors, like liquidity, calendar effects and oil. The authors show that high-liquidity days are indeed associated with herding, which is consistent with the existing evidence in the academic literature (Galariotis et al., 2016). Moreover, contributing to the literature, the authors provide evidence that herding during high-liquidity days is driven by fundamental factors and is, hence, a rational response of investors to changes in information, which should not distort the market. A novel evidence is also obtained with respect to herding during macroeconomic news releases. Similar to previous researches, we find herding during these days to exist. Adding to existing empirical evidence, the authors conclude that it is driven by both rational and irrational factors, which indicates that asset prices may deviate from their fundamental values around these days. Apart from that, the authors also show that herding in Moscow Exchange is not associated with extreme down oil price movements, but rather with extreme spikes in it, which adds to scarce empirical evidence on this issue.

Finally, we extend the study to a new and rather peculiar geographical setting, Moscow Exchange, which enhances empirical evidence on herding in the context of emerging markets. The authors show, that Russian stock market does not yet belong to the same group with the world's most profound markets. It is still in a development stage and exhibits herding trends that are similar to those of some European markets, based on the evidence from other studies.

The findings presented in this paper should be of a particular importance for investors with positions in MICEX-traded stocks. Making their investment decisions, these participants of financial markets should consider the fact that Moscow Exchange exhibits traces of irrational herding behaviour, especially in down days and during the periods of market turmoil and uncertainty. These irrational patterns are likely to cause asset mispricing, which will adversely impact an investor's portfolio diversification capabilities: in the presence of irrational herding, investors would need more assets to reach the same level of portfolio diversification. Apart from investors, our findings are likely to be of interest for regulatory bodies on Moscow Exchange. The signs of regular irrational herding might indicate that investors in Russia might be facing certain obstacles with obtaining information and are, hence, forced to herd. Taking additional steps towards creating a more transparent market should improve the situation around herding, which, in its turn, will create more incentives to invest in Russian companies and contribute to an overall development of Moscow Exchange. Finally, our findings should be interesting to researches exploring the phenomenon of herding in the context of emerging markets, especially in what pertains to the novel evidence of the factors associated with herding.

5.4 Limitations of the study

It is important to consider limitations of this paper while interpreting the results of the current research. First of all, due to data limitations, the authors of this study do not look into the most recent time periods, e.g. 2016. This is so because the quality and precision of book-to-market ratio reported in Thomson Reuters Datastream for this year is questionable. Book-to-market ratios are used by the authors for a construction of SMB, HML and momentum factors; and are, thus, an important input for our quantitative analysis. To avoid bias in the results, the authors limit the research to the period of 2008-2015, which still allows the authors to incorporate most turbulent and significant events in our sample. An additional limitation with respect to the data pertains to the time horizon of stock returns studied. The current paper treats herding as a short-term phenomenon and consequently uses daily stock returns to infer the information from the market. The authors do not study effects of herding over longer time horizons, which might be treated a suggestion for future research.

Another limitation connected to data availability pertains to dates of macroeconomic announcements. The authors of this paper aim at using the most reliable and precise data and, hence, use information from the most credible sources. As, to the best of the authors' knowledge, there is no governmental electronic source for this type of data, the authors extract the information from Financial Times Economic Calendar (Financial Times, 2017). This resource tracks the dates of important macroeconomic announcements for Russia starting from 2011, hence, our analysis of the market's reaction to these events pertains to the period of 2011-2015. The authors still believe that our results may be generalized to the whole sample studied in this paper, as it exhibits similar patterns of herding behaviour across time.

It is important to mention that the results of the analysis presented in this paper relate to Russia only. Based on empirical evidence in academic literature, one may conclude that herding is a peculiar phenomenon that has proven to be rather country- and culture-specific. In the case of Russia, the authors where unable to identify any group of countries similar enough to justify their inclusion into the analysis. For instance, we do not analyze herding for the whole BRICS bloc, as it is, in effect, represented by countries that are substantially different geographically, economically and culturally. Apart from that, a limitation comes from different currency returns at Moscow Exchange. This paper is especially relevant for investors with returns denominated in Russian roubles, while investors with returns in foreign currency should treat the results with caution due to an existing foreign exchange risk.

Finally, geographical and cultural differences in herding patterns do not allow us to test the robustness on a different geographical sample. Some papers, e.g. Chang et al. (2000) suggest that robustness may be checked by splitting the sample into different subgroups; in their paper the authors do the split according to company size. In our research design, tests on size and number of analysts following a company constitute a separate part of the research. As seen in Section 5, they do provide results consistent with those of the full-sample regression.

6. Conclusion

The research presented in this paper has been motivated by growing amount of evidence on behavioural biases, which contradicts propositions of the Efficient Market Hypothesis. The authors of the paper focus particularly on examining herding towards the market – a type of investor behaviour, which leads them towards mimicking each other's actions and results in lower-than-efficient dispersion of asset returns on the market. We choose to investigate herding phenomenon in the context of Russian stock exchange, which has a reputation of a relatively developed market, yet is surrounded by concerns of low investor protection and asymmetric information. The purpose of the research is to identify whether herding is present in Moscow Exchange, and, if so, test for factors that might be potentially associated with its formation. Contrary to most academic works on the issue of herding, the authors of this paper conduct the analysis specifically taking into account different underlying mechanisms of herding behaviour, splitting it into spurious and irrational parts. This allows the paper to present a more comprehensive and all-around picture of herding in Moscow Exchange.

The most important finding of the current research paper unveils that herding does exist in Russian stock market on a daily basis and is driven by investors' behaviour during the days of negative market returns. Moreover, this tendency to mimic the market appears to be propelled by non-fundamental mechanisms and is, hence, irrational in its essence. Apart from that, the authors find evidence that irrational herding towards the market in Russia is especially pronounced during periods of market turmoil and increased uncertainty (e.g. financial and geopolitical crises), macroeconomic news releases and extreme upward oil price movements. Apart from that, the findings indicate that irrational herding might be associated with small companies. Spurious herding is detected during the days of sanctions announcements, macroeconomic news releases and high-liquidity days.

As discussed in Section 5, the findings of this paper should be of a particular interest for investors in MICEX-traded companies, as the paper elicits more light on the underlying mechanisms of Moscow Exchange, indicating periods of likely asset mispricings; regulatory bodies supervising Russian financial market, as the paper points out to potential problems with obtaining information on the market; and researchers exploring the phenomenon of herding in the context of an emerging market, as the paper enhances empirical evidence on the issue of herding and factors associated with it in the context of an emerging market.

A potential direction for further research might lie in testing additional factors associated with herding towards the market. Apart from that, researchers might find it helpful to look into other factors that might capture fundamental information on the market. Incorporating them into the research, would imporove results precision. Additionally, one might consider looking more profoundly at the relationship between information environment and market-wide herding. The results of the tests presented in this paper do not give definitive conclusions, but suggest that some association might exist.

7. References

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8. Appendices

Appendix A. Description of Christie & Huang (1995) CSSD herding methodology

Christie & Huang (1995) propose to detect herding by looking at the relationship between market returns and cross-sectional standard deviation (CSSD) of asset returns. The Cross-sectional standard deviation is defined as in Equation N:

$$CSSD_t = \frac{\sqrt{\sum_{i=1}^{N}(R_{it} - R_{mt})^2}}{N-1} \tag{A.1}$$

where N indicates the amount of companies in a selected portfolio, R_{it} represents returns of a company i at time t and R_{mt} gauges return of an equally-weighted market portfolio. The variable demonstrates how closely on average asset returns are distributed around market returns.

It is important that CSSD is not a measure of herding by itself – it is the relationship between it and returns of a market portfolio that indicates the presence of herding. As pointed out by Christie & Huang (1995), rational asset-pricing models predict that the dispersion of individual asset returns should become higher with an increase in absolute market returns, i.e. there should be a positive relationship between cross-sectional standard deviation and absolute market returns. This pattern occurs due to different sensitivities of assets to market return: some stocks tend to be more volatile than the market, while others are less. However, if investors herd towards the market, the relationship should turn negative. In this case, with an increase in market returns, CSSD will grow at a decreasing rate or, in a case of a strong herding pattern, even decrease.

Christie & Huang (1995) hypothesise that investors are most prone to mimicking the market and exhibiting market-wide herding in times of severe market stresses and periods of extreme market movements. To test for herding behaviour during extreme market movements, the authors establish the following model:

$$CSSD_t = \beta_0 + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t \quad , \tag{A.2}$$

where dummy variables D_t^L = 1 if market returns on day t are located in an extreme lower tail of return distribution, and equals 0 otherwise; $D_t^U = 1$ if the market returns on day t are located at an upper tail of return distribution, otherwise both dummy variables take value of zero; β_0 is an intercept and ϵ_t - an error term. The boundaries determining extreme market movements are set arbitrarily. Christie & Huang (1995) classify 1 and 5 top and bottom percent of return observations as extreme market movements. The presence of market-wide herding is indicated by significant and negative beta coefficients.

Appendix B. Description of companies in the sample by size and industry

Industry	**Number of firms**	**Average market capitalization**	**Share of sample's market capitalization**	**Share of total market capitalization**
Chemicals	7	171,345	4.19%	3.59%
Electricity	22	43,283	3.33%	2.85%
Finance	10	293,912	10.27%	8.80%
Food products	7	24,636	0.60%	0.52%
Manufacturing	10	338,814	11.84%	10.15%
Metal	10	138,404	4.84%	4.15%
Other natural resources	10	366,287	12.80%	10.97%
Oil & Gas	8	1,363,338	38.12%	32.67%
Pharmaceuticals	4	27,425	0.38%	0.33%
Retail and Wholesale	5	278,601	4.87%	4.17%
Services	13	141,354	6.42%	5.50%
Others	14	47,573	2.33%	2.00%
Total	**120**		**100.00%**	**85.71%**

Table B.1. The table represents the market size of the companies included in the sample as of December 30, 2015. Data for average market capitalization are in millions of Russian roubles.

Appendix C. List of macroeconomic announcements used in the study

№	**Announcement**
1	GDP growth, % (monthly and annually)
2	Consumer Price Index developments
3	Producer price index developments
4	Key interest rate announcements
5	OPEC monthly oil market reports
6	Sovereign Debt ratings
7	OECD Economic Outlook
8	Important international meetings (G7, G20, BRICS, etc.)
9	Trade balance announcement
10	Unemployment developments
11	Real wage growth
12	Retail sales growth

Table C.1. The table represents the list of macroeconomic announcements used in the current study.