HERDING IN INVESTOR’S BEHAVIOR

An investigation of herd behavior in the Russian stock market

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This paper provides a comprehensive study of herding behavior in the Russian stock market. In that way, it contributes to literature on investors’ herding behavior in the following aspects. First, it extends studies of investors’ herding to an emerging market, not yet being thoroughly investigated. Second, it combines the implications of previous researches into the relationships with herding, thus, investigating the effect of the direction of the market movement, extreme market returns, and the Russian financial crisis, on herd behavior respectively. By applying daily returns of the MICEX Index and its constituents from January 8, 2005, through, December 31, 2009, no significant evidence was found in favor of herding behavior over the whole dataset. However, there is some evidence that suggests that herding behavior shows asymmetric effects in the Russian stock market, since it was analyzed to be more present during downward directions of the market, compared to upward directions. No evidence was found for either extreme market returns or the Russian financial crisis with herding activity. Due to the scope of this research, it is suggested that future researches take into account the effects of the international integration of the Russian stock market, oil prices, and political news when investigating this stock market.
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CHAPTER 1 - INTRODUCTION

This paper concerns a bachelor thesis assigned by the department of Finance of Tilburg University. The thesis is about the extent of herd behavior in the Russian stock market. This chapter introduces the problem statement, followed by the research questions, the data collection, and an outline of the structure of the paper.

1.1 Problem indication

As the economic environment is constantly changing and experiencing periods of economic uncertainty, so do the influences on the decision-making process of investors change. One such influence that has received particular attention in the last decade is the concept of ‘herding’. While herd behavior itself pertains to the instinct of animals to follow the herd, diverse set of theoretical approaches have allowed the concept to be applied to many domains. Relating to the field of behavioral finance, herding behavior is generally characterized by mimicking the actions of other investors, which constitute the market consensus (Bikhchandani & Sharma, 2001). Even though the motivations behind the phenomenon are explained from several perspectives, there is a general conformity concerning its effect in financial markets, referring to substantial movements in asset prices and increasing price volatility (Chang, Cheng, & Khorana, 2000). It is these effects, together with the policies that should be in place to deal with the problem, that were of main interest in the growing body of literature.

In addition, multiple researches on herd behavior have been conducted, validating the existence or absence of it in specific stock markets. A summary of several results is given, because of their relevant contribution to this research. First, research has proven that the characteristics of an emerging market make herd behavior more likely, in comparison with a developed market, to be encountered in such a market (Chang et al. 2000; Lao & Singh, 2010; Economou, Kostakis & Philippas, 2011). In addition, Lao and Singh (2010) provided evidence for asymmetric effects of herd behavior patterns. This implies that investors tend to herd more intensively during either an upward movement or a downward movement of the market. Furthermore, it has been suggested that the presence of herd behavior is most likely to occur during periods of extreme market movements, as investors would then
be more triggered to follow the market consensus (Chen, Demirer & Kutan, 2010). According to recent experience, this result is also relevant for the effect of a financial crisis on the extent of herding, since extreme return movements persistently occur in such periods (Chiang and Zheng, 2010). At last, the effect of the market capitalization of firms on the tendency to herd, indicating that herd behavior is more profound among smaller stocks compared to heavily-followed larger cap stocks (Bikhchandani and Sharma 2001). These results are more thoroughly discussed within the literature review-section.

The above-mentioned findings triggered the motivation to investigate the relationships with herd behavior in a specific stock market, thereby, combining the approaches of multiple researches. The Russian stock market has been chosen as the setting of investigation for the following reasons. First, Russia is considered to be one of the emerging markets (being part of the ‘BRICs’ economies), expecting to be a major economic power around the year of 2050. This makes it interesting to test whether indeed herd behavior is to be more profound in such an emerging market. Second, to my knowledge, the effect of herding behavior in this market is not thoroughly investigated. Therefore, the contribution of this research is of academic relevance, since it provides more insight into the effect of herd behavior on asset prices in the Russian stock market, while also investigating the several influences on the extent of herding.

1.2 Problem statement

As discussed, the concept of herding is applied on the Russian stock market. Subsequently, the problem statement of this paper is formulated as follows:

➢ “To what extent does herding behavior affect the Russian stock market?”

1.3 Research questions

Due to the scope of this research, only three relationships with herding behavior within the Russian stock market are investigated. Being so, an attempt has been made to solve the problem statement. Consequently, the research questions are stated in the following manner:
i. Does the direction of the market movement have an effect on herd behavior in the Russian stock market?

Research in Chinese stock markets implied that the level of herding behavior is asymmetric during different market returns (Chiang, Mason, Nelling & Tan, 2007). This implies that investors tend to herd more intensively during either an upward movement or a downward movement of the market. It is expected that patterns of herd behavior are more profound during a specific direction of the market movement, validating the existence of asymmetries.

ii. Do extreme market returns affect herd behavior in the Russian stock market?

Herd behavior in the Russian stock market is expected to be more profound during periods of extreme market returns. In this way, those extreme market returns represent returns that are significantly above (below) the average market return.

iii. Did the recent Russian financial crisis affect the extent of herding in the Russian stock market?

As previous researches have discussed, periods of financial crisis are characterized by fluctuating market returns. Therefore, herding behavior is expected to be more explicitly present during the Russian financial crisis of 2008, compared to periods outside this time frame.

It seems that the latter two research questions somewhat overlap. However, it must be noted that they both contribute to the problem statement in a very distinct way. By means, the effect of extreme market returns on herding behavior is investigated over the whole sample period, while the effect of the Russian financial crisis is investigated within a specific timespan. Further distinction between the two approaches is made within the methodology section.
1.4 Conceptual framework

The problem statement and the corresponding research questions can be summarized in the following conceptual framework.

1.5 Research design and data collection

The approach that is employed in this research, in order to detect and measure herding behavior, is the Cross Sectional Absolute Deviation proposed by Chang et al. (2000). This approach is based on the relationship between CSAD and return dispersion, and the belief that herd behavior would lead security returns not to deviate far from the overall market return. The dataset contains the daily stock prices of the 30 major and most liquid Russian stocks, contained in the Moscow Interbank Currency Exchange index (MICEX), covering a period range of January 2005 – December 2009, thereby including the recent financial crisis period of 2008. This data was retrieved from Thomson Reuters Datastream database.

1.6 Structure of the thesis

The remainder of this paper is organized as follows. Section 2 covers a review on previous researches on herd behavior in stock markets and its implications. Section 3 provides more insight on the methodology and data collection. Section 4 provides the empirical findings on the existence and extent of herd behavior in the Russian stock markets. At last, Section 5 presents a summary of the paper in addition with the most remarkable conclusions and the limitations of the research.
CHAPTER 2 – LITERATURE REVIEW

Over time, the growing body of academic research on investor’s herding behavior has led us to understand the motivations behind the phenomenon. Before discussing these motivations, it is important to distinguish the concept from normal market behavior, thereby, contrasting spurious and intentional herding (Devonow & Welch, 1996). Thereafter, the results of the previous empirical studies, mentioned in the introduction, are more thoroughly discussed, while also the measures of herding have received particular attention.

2.1 Spurious vs. Intentional herding

Bikhchandani and Sharma (2001) described spurious herding as an efficient outcome of groups that take similar decisions, when confronted with similar decision problems and information. This type of herding is fundamental-driven in a sense that, for example, a sudden increase in interest rates and a loss of attraction of stocks, could result in a smaller percentage of stocks in investors’ portfolios. This is not herding, as a consequence of following other investors’ decision, but merely a reaction to commonly known public information.

Contrarily, intentional herding is the result of an obvious intent by investors to copy the behavior of other investors (Bikhchandani & Sharma, 2001). While spurious herding usually leads to efficient decision-making, intentional herding need not to be. Although the distinction between these two types of herding is of high importance, studies have experienced difficulties in empirically distinguishing between them.

2.2 Irrational vs. rational herding

Now that the two types of herding have been discussed, it is logical to relate those to the motivations behind the phenomenon. In general, literature has identified two motivations of herding behavior in stock markets, both construing it as either being of a rational or irrational form (Chang et al., 2000). Since the focus of this paper is on herding behavior by investors in stock markets, it is relevant that we relate the motivations of herding to such a setting and not financial markets in general, thus, excluding agent-related herding, reputation-based herding, etc.
According to Devonow and Welch (1996), on the one hand, irrational herding can be explained from a psychological point of view, in which investors disregard their own information and blindly follow other investors’ decisions. Previous studies have identified several explanations of irrational herding by investors. Christie and Huang (1995) argue that investors are more likely to herd during market stress. The reasoning behind this stems from the intrinsic preference of humans for certainty and conformity. Following the market consensus in times of uncertainty reduces an investor’s concern of making incorrect decisions, highlighting the disability of rational analysis. This approach is further supported by Devonow and Welch (1996), who argue that investors feel a sense of security in following the crowd, even if that implies that they have to disregard their prior beliefs.

The rational approach, on the other hand, relates to the intentional action of individuals to follow other investors (as described as intentional herding in the subsection above). Bikhchandani and Sharma (2001) refer to this approach as the outcome of information learning and informational cascades. This occurs when investors face similar investment decisions and when there is uncertainty about the quality of public information. Consequently, each individual has a private assessment of the quality of the publicly available information. The result is that investors observe each other’s actions, to make inferences about the private assessment of information by others, up to a point where they intentionally and rationally base their decision on the previous actions of others. To illustrate, an individual generally ends up in an invest (reject) cascade if and only if the number of predecessors who invest is greater (less) than the number of predecessors who do not invest by two or more (Bikhchandani and Sharma, 2001). For example, an investor that receives clear signals not to invest in a particular asset might ignore this information in favor of the observation that the three prior investors did invest. Since the decision is based on the actions of others, one’s private information is not added to the public pool of knowledge, thus, creating negative externalities for subsequent investors. Not surprisingly, information cascades often lead to inefficient outcomes, which main source is the dependence on sub-optimal initial events. It should be mentioned that this explanation is just theoretical and it is hard, if not impossible, to apply it to practice. This is mainly due to difficulties experienced in ascertaining how the signals, received by an individual investor, are interpreted.
An explanation of investor’s herding behavior that is not rational, neither fully irrational, is based on positive feedback training, also known as momentum-investment strategies. This concerns the tendency of investors to continuously buy good-performing stocks and sell the poor performing ones. Nofsinger and Sias (1999), relate high levels of this strategy to herding in a financial setting, in a sense that institutional and individual investors often trade in the same direction over a period of time. This approach is perceived to be found in between the irrational and rational explanation, for it is partly adopted with the rational and intentional action to benefit from the strategy. On the other hand, it is also applicable to noise traders, which refer to stock traders whose investment decisions are irrational and irregular. Their presence in stock markets can cause severe price movements, thereby, adding to volatility even if all other traders behave rational De Long, Schleifer, Summers & Waldman, 1990).

Hence, while irrational herding explains the phenomenon from a psychological point of view, rational herding refers to intentional actions, often the result of information cascades. Positive feedback training is an explanation that can be found somewhere in between.

2.3 Importance of understanding investor’s herding behavior

The discussion on the types and dimensions of herd behavior in a financial setting already implicates some reasons why it is important to understand the concept. For it may not be clear instantly, these reasons are more thoroughly highlighted below. The main reason for examining investor’s herd behavior in financial markets is that it provides us with a higher degree of understanding with respect to its influence on asset prices. Chang et al. (2000) provides support for this argument by discussing this substantial effect of investors’ herding on share prices. Referring to the discussion above, intentional herding does not need to be efficient, and usually refers to fragile and sensitive markets. Additionally, the presence of noise traders, being part of a herding group, can cause severe price movements and volatility. Being so, herding behavior is often referred to as market inefficiency, contradicting the efficiency of the asset valuation process explained by rational asset pricing models (Lao & Singh, 2010).
Second, investigating herding behavior allows us to further understand the influences on the decision-making process of investors, whether approached from a rational or irrational point of view. Even though, these psychological processes are difficult to investigate, it still provides a deeper insight into the concept of herding behavior and draws attention for future investigations.

At last, a more thorough understanding of the concept allows us to distinguish intentional herding from spurious herding, in which the latter one does not result in market inefficiency and affected stock prices.

2.4 Empirical studies

After discussing the theoretical background of herding in stock markets, it is also important to look at the most significant results of the empirical studies that have been conducted so far.

First, research has proven that the characteristics of an emerging market make herd behavior more likely, in comparison with a developed market, to be encountered in such a market (Economou, et. al 2011). According to Bikhchandani and Sharma (2001), the relative lack of transparency in these markets, weak reporting requirements, lower accounting standards, lax enforcements of regulations, and costly information acquisition inevitably lead to herd behavior. In addition, Chang et al. (2000) find similar results, collecting significant evidence of herding in South Korea and Taiwan, the two emerging markets in their sample, compared to the US, Hong Kong, and Japan, the developed markets in their sample. A more recent research, based on data from 1999-2009, also provides an empirical evidence of herd behavior on the emerging markets in Asia (two BRIC countries), more precisely the Chinese and Indian markets, validating the previous mentioned statement (Lao & Singh, 2010).

Second, the effect of the market capitalization of firms on the tendency to herd, indicating that herd behavior is more profound among smaller stocks compared to heavily-followed larger cap stocks (Bikhchandani & Sharma 2001). McQueen, Pinegar, and Thorley (1996) imply that large stocks (in terms of market capitalization) tend to respond much quicker to good news, compared to small stocks. Theoretically, this is due to the lack of information on these small stocks, fewer analyst recommendations, and a less firmly grounded market consensus.
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Third, there are been significant results suggesting that herd behavior patterns are affected by the direction of the market movement, thus, referring to either bull or bear markets. However, these results are restricted to specific stock market characteristics. Lao and Sing (2010) identified that herding behavior in the Chinese market is greater when the market is falling, in contrast to the results on the Indian market, where herding behavior was more profound during rising periods of the market. Therefore they supported the conclusion by Chiang et al. (2007), who stated that the level of herding behavior is asymmetric during different market returns in Asian markets.

At last, it has been suggested that the presence of herd behavior is most likely to occur during periods of extreme market movements, as investors would then be more triggered to follow the market consensus (Demirer et al., 2010). In this way, extreme market returns refer to abnormal market returns over a specific time range. Lao and Singh (2010) investigated this relationship for the Indian and Chinese market, by comparing herd behavior test results during normal market returns with those under extreme upward or downward market movements, relating to three cut-off criteria. They concluded the presence of more severe herding behavior during market stress, explained from the irrational behavior by inexperienced individual investors who are easily misled by media and blinded by greed and envy. Additionally, recent experience suggests that the extreme market return movements have endured to occur in periods of crisis. This makes it relevant to investigate the effect of such a financial crisis on behavioral herding patterns. In a study on herd behavior in global stock markets by Chiang and Zheng (2010), evidence suggested that crisis triggers herding activity in the crisis country of origin and then produces a contagion effect, which spreads the crisis to neighboring countries. The relationship can be explained from the human tendency for conformity and security in times of uncertainty. The scope of the recent financial crisis provides an opportunity to further investigate this contagion effect using more recent data.
Previous empirical researches have also implications for the design of this research, in a sense that several methods of measuring herding in stock markets have been proposed. Bikhchandani and Sharma (2001) argue that these methods of herd behavior are statistics-based, focusing on clustering of decisions. It therefore lacks in recognizing the direct linkages between the types of herding, intentional and spurious, and the empirical design used to test for herding. Their explanation behind this is that it is difficult to assert the true fundamentals of herding, and that it is difficult to measure and quantify them.

Lakonishok, Shleifer, and Vishny (1992) defined and measured herding as the average tendency of a group of investors to buy or sell particular stocks at the same time, parallel to the expectations of independent actions. It thereby aims at identifying correlation in trading patterns, which need not implicitly represent herding. The method has been criticized for disregarding the amount of stock traded, while focusing on the number of investors, and for its shortcomings in identifying intertemporal trading patterns (Bikhchandani & Sharma, 2001).

Wermers (1999) introduced a new method of measuring herding, the so-called portfolio-change measure of correlated trading. The model defined herding by the extent to which portfolio-weights, assigned to the various stocks by different investors, move in the same direction. Thereby it improves the model proposed by Lakonishok et al. (1992) in its first respect, while it has received criticism for yielding results based on spurious herding.

Thereafter, a growing body of literature analyzed herding in stock markets using measures of dispersion around the market return during periods of significant changes in stock prices (Christie and Huang, 1995; Chang et al., 2000; Tan et al., 2008, etc.). Christie and Huang (1995) provided reason for this by arguing that during periods of market pressure movements, stock returns have the tendency to be more clustered, thereby, indicating a co-movement of stock prices, which is independent of their fundamental characteristics. These periods over market stress are then characterized by the formation of herds, since individual investors have a higher tendency to suppress their own beliefs and follow the market consensus. Consequently, cross-sectional dispersion of returns is predicted to be low in the presence of herding behavior by investors.
More recently, Hwang and Salmon (2004) aimed more towards the cross-sectional variability of factor sensitivities. Their formulation of a herding measure related to the relative dispersion of the betas for all assets in the market.

A deeper insight of the dispersion-based measures of herding, together with an alternative proposed by Chang et al. (2000), is provided in the next section, since these methods are the foundation of this research.
CHAPTER 3 – METHODOLOGY

The objective of this research is to find evidence on the relationship between herd behavior in the Russian stock market and the sign of the market return, extreme market returns, and the recent financial crisis. In this study, the largest Russian stock exchange, MICEX Stock Exchange, is selected because it is the most representative stock exchange of Russia. The stock exchange opened in 1992 and was the leading Russian stock exchange. As of December 2010, about 239 Russian companies were listed, representing a market capitalization of US$950 billion. Among these are major companies such as Sberbank, Gazprom, Rostelecom, LUKoil, Rosneft and others. Additionally, it is the largest stock exchange in the Commonwealth of Independent States (CIS), Eastern and Central Europe, and is among the world’s top 30 stock exchanges. As a result, the MICEX Index, calculated since 1997, is the main indicator of the Russian stock market. It is comprised of the 30 most liquid and most rapid-developing Russian companies, representing the main sectors of the country’s economy. Furthermore, the family of the MICEX Stock Exchange’s stock market indices include both multiple sectorial, as well as capitalization ones. Being so, it contributes to the development of a competitive stock market in Russia, and the creation of an international financial center in Moscow. As of December 2011, MICEX merged with Russian Trading System, expected to create a single Russian entity.¹

3.1 Adopted measurement of herding

As discussed, the adopted measurement of herding in this research is based on the return dispersion model by Chang et al. (2000). Before arguing the implications of this model, a more solid background is provided by discussing the return dispersion model of Christie and Huang (1995) and how it transformed into the model of Chang et al. (2000).

Both models analyze herding in terms of cross-sectional stock returns, implying that herd behavior would lead security returns not to deviate far from the overall market return. The measures aim at the detection of herd behavior in periods of extreme upward or downward movement in returns. However, since the presence

¹ Information about MICEX was retrieved from: http://www.micex.com/group/lbmmvb/profile
of herding behavior is not restricted to such periods only, it is also necessary to investigate how this phenomenon evolves over time. It has also been discussed that it is hard to distinguish different types of herding using different measures, since the true fundamentals are difficult to ascertain. Therefore, the cross-sectional methods for asset returns allow to investigate herding using a market-based examination in a sense that it focuses on the closing gap between individual stock returns and the market return.

Christie and Huang (1995) estimated the cross-sectional standard deviation (hereafter referred to as CSSD) of individual stock returns with respect to market returns. It is expressed as:

\[
CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2}{N-1}}
\]

Here, \( R_{i,t} \) is the observed stock return of firm \( i \) at time \( t \), \( R_{m,t} \) is the cross-sectional average return of the market portfolio at time \( t \), and \( N \) is the number of stocks in the market portfolio. Next, the CSSD of return was regressed against a constant and two dummies, in order to identify the extreme market phases. Here, \( D_L \) equals 1 if it lies in the extreme 1% and 5% lower tail of the same distribution, and is equal to zero otherwise. The same holds for \( D_U \) in the case of the upper tail:

\[
CSSD_t = a + b_1D_L + b_2D_U + e_t
\]

Where the \( a \) coefficient denotes the average dispersion of the sample excluding the regions corresponding to the two dummy variables. According to this approach, herding behavior is present in the case of statistically significant negative values for \( b_1 \) and \( b_2 \).

It contrasts with rational asset pricing models, which predict an increase in dispersion because individual assets differ in their sensitivity to the market return. Despite of being an intuitive measure of capturing herding, it has been remarkably affected by the existence of outliers. As a consequence, Christie and Huang (1995) proposed the use of the cross-sectional absolute deviation (hereafter referred to as CSAD), as a more solid measure of return dispersion:
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\[ \text{CSAD}_t = \frac{1}{N} \sum_{i=1}^{N} |r_{i,t} - r_{m,t}| \]  \hspace{1cm} (3)

Here, \( N \) is the number of firms in the aggregate market portfolio, \( r_{i,t} \) is the observed stock return on firm \( i \) for day \( t \), and \( r_{m,t} \) is the cross-sectional average return on day \( t \). Relating this to equation (2) results in the following:

\[ \text{CSAD}_t = a + b_1 D_L^t + b_2 D_U^t + e_t \]  \hspace{1cm} (4)

Again, \( D_L^t \) equals 1 if it lies in the extreme 1% and 5% lower tail of the same distribution, and is equal to zero otherwise. The same holds for \( D_U^t \) in the case of the upper tail.

Alternatively, Chang et al. (2000) proposed a related approach to the one suggested by Christie and Huang (1995), using the entire distribution of market returns. This approach is the basis of this research in a way that it is used as the main regression while it also provides the foundation for the subtests. It is stated in the following equation:

\[ \text{CSAD}_t = \alpha + \gamma_1 |r_{m,t}| + \gamma_2 r_{m,t}^2 + \epsilon_t \]  \hspace{1cm} (5)

Thus, the relationship is based on the CSAD and the market return \( (r_{m,t}) \) in order to detect herd behavior. Standard asset pricing models, like the CAPM, assume that returns’ dispersion is linearly related to market return, so when herding is absent one would expect a positive value of coefficient \( \gamma_1 \). However, when herding is encountered during times of extreme market movements, the cross-sectional dispersion of stock returns is expected to decrease or increase considerably less than proportional with market return, as linear asset pricing models would indicate. As a consequence, the squared market return is introduced as an additional term in the regression in order to capture this nonlinear relationship through a negative estimate of the coefficient \( \gamma_2 \).
3.2 Tests of herding

In order to answer the research questions, which surround the problem statement, four tests have been performed, including the main test over herding as well as subtests of herding under alternative criteria. The alternative approaches are adopted to test for the effects of the direction of the market movement, extreme market returns, and the Russian financial crisis on herding, respectively. Due to the scope of this research, it has been chosen to restrict only to these areas, thereby excluding tests of the effect of market capitalization on herding behavior. The subtests follow the approach proposed by Lao and Singh (2010).

3.2.1 The main test of herding behavior in the Russian stock market

For the main test of herding behavior in the Russian stock market, the basic model proposed by Chang et al. (2000), mentioned in the previous section, is applied. With respect to this model, we can formulize the hypothesis as follows:

**H1 - Main test.**  
In the presence of herding, it is expected that $\gamma_2 < 0$ in model 5.

3.2.2 Herding behavior during different directions of the market movement

It has been suggested that the direction of the market movement has an effect on the relationship between CSAD and the market return, referring to herding behavior being more likely to present in either bull or bear markets. To test for this asymmetry, the dataset is divided based on either of the two instances (increasing/decreasing market returns) and analyzed separately as in Chiang et al. (2007). In accordance with the approach to examine the asymmetric effect of the market return sign, this results in the following models and hypotheses:

\[
\text{CSAD}_{i}^{\text{Down}} = \alpha + \gamma_1 |r_{m,i}^{D}| + \gamma_2 (r_{m,i}^{D})^2 + \epsilon_i \quad \text{if } r_{m,i} < 0 \quad (6)
\]

\[
\text{CSAD}_{i}^{\text{Up}} = \alpha + \gamma_1 |r_{m,i}^{U}| + \gamma_2 (r_{m,i}^{U})^2 + \epsilon_i \quad \text{if } r_{m,i} \geq 0 \quad (7)
\]
Where: $\gamma^D_2 (\gamma^U_2)$ is the coefficient of the value-weighted market portfolio return at time t when the market declines (increases), and $r_{m,t}^{Down} (r_{m,t}^{Up})$ is the value-weighted market portfolio return at time t when the market decreases (increases).

**H2 – Market return sign.** In the presence of herding, it is expected that $\gamma^D_2 < 0$ and $\gamma^U_2 < 0$, with $\gamma^D_2 < \gamma^U_2$, if this behavior is more pronounced during days with negative market returns, in model 6 and 7 respectively.

### 3.2.3 Herding behavior during extreme market returns

To test for herding behavior during extreme market return, a dummy variable is introduced to indicate whether the market return on a specific day lies in the extreme upper (lower) tail of the distribution. In this study, 1 percent, 5 percent, and 10 percent are used as criteria for extreme market returns. This results in the following model and hypotheses:

$$
CSAD^L_{t,Down} = \alpha + \gamma_1 |r_{m,t}| * D^L_t + \gamma_2 r^2_{m,t} * D^L_t + \epsilon_t \quad \text{if } r_{m,t} < 0 \quad (8)
$$

$$
CSAD^U_{t,Up} = \alpha + \gamma_1 |r_{m,t}| * D^U_t + \gamma_2 r^2_{m,t} * D^U_t + \epsilon_t \quad \text{if } r_{m,t} \geq 0 \quad (9)
$$

Where: $D^L_t = 1$, if the market return on day t lies in the extreme lower tail of the distribution; and equal to zero otherwise, and $D^U_t = 1$, if the market return on day t lies in the extreme upper tail of the distribution; and equal to zero otherwise.

**H3 – Extreme market returns.** In the presence of herding, it is expected that $\gamma_2 < 0$. Furthermore, it is expected that in the case of herding, it is more severe than in model 5 compared to model 8 and 9, thus, $\gamma_2 (8/9) < \gamma_2 (5)$. 
### 3.2.4 Herding behavior during the Russian financial crisis

At last, the effect of the financial crisis on herding behavior in the Russian stock market is tested. Recall that herding behavior may be more quickly encountered during times of high market uncertainty. Therefore, testing for herd behavior for the period before the Russian financial crisis, compared to that during the financial crisis, should provide evidence for this. The period before the financial crisis in the sample refers to January 8th, 2005 to December 31st, 2007, while the period during the financial crisis is captured within the time frame of January 1st, 2008 to December 31st, 2008.

\[
\text{CSAD}_{\text{Before}} = \alpha + \gamma_1 |r_{m,t}| + \gamma_2 r_{m,t}^2 + \varepsilon_t \quad \text{for } t = 08/01/2005 - 31/12/2007 \quad (10)
\]

\[
\text{CSAD}_{\text{During}} = \alpha + \gamma_1 |r_{m,t}| + \gamma_2 r_{m,t}^2 + \varepsilon_t \quad \text{for } t = 01/01/2008 - 31/12/2008 \quad (11)
\]

**H4 – Financial crisis.** In the presence of herding, it is expected that \( \gamma_2 < 0 \), with \( \gamma_2 (11) < \gamma_2 (10) \), if herding is more profound during the Russian financial crisis period.

### 3.3 Data

The dataset used in this study covers the period between January 2005 and December 2009 and consists of the MICEX Index and its constituents. In this way, the MICEX Index is used as the value-weighted return of the market portfolio \( (r_{m,t}) \), while the constituents’ returns represent the individual stock returns \( (r_{i,t}) \). The idea behind the time frame is that it allows investigating the phenomenon over a significant dataset, while it also captures the financial crisis period of 2008. This specific period is relevant, since it represents extreme market movements, which will be relatively important for this research. Important to note is the changing composition of the index over the years. When obtaining the data, it was ensured that these changes were reflected in the dataset, thereby dividing the total dataset into several subsets when calculating the CSAD, and combining them afterwards. In the study, a total of 1213 daily return data calculated on the basis of the prices of each stock and the index were analyzed using the regression method. The data used for analysis was obtained from the Thomson Reuters Datastream database.
CHAPTER 4 – RESULTS

This chapter discusses the results of the regressions that were introduced in the previous section. These regressions are discussed in separate sections, since this allows the results to be related to the research questions in an organized manner. In that way, the research questions are used in an attempt to answer the problem statement in the concluding section.

Table 1 reports the descriptive statistics of the CSAD and the market return ($r_m$). It immediately becomes clear that the market return fluctuates substantially, covering a range of approximately 47%. This range is not exceptional when taking into consideration the contagion effect of the Russian financial crisis that started in the US. This results in significant decreasing market returns, in which the minimum value of -18.7% was found on October 6, 2008, not surprisingly within the time frame of the financial crisis. It should be noted that these maximum and minimum represent extreme market returns, and that their influence as outliers in the regressions are considered. Being so, the dataset was winsorized at the 98% level as well as winsorized based on the interquartile range (IQR). This yielded no significant difference in results, so that their contribution is not worth noting.2

Table 1 – Descriptive statistics of CSAD and the market return ($r_m$)

<table>
<thead>
<tr>
<th></th>
<th>CSAD</th>
<th>$r_m$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.7097</td>
<td>0.1225</td>
</tr>
<tr>
<td>Median</td>
<td>1.4258</td>
<td>0.1586</td>
</tr>
<tr>
<td>Maximum</td>
<td>14.3750</td>
<td>28.6932</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.4307</td>
<td>-18.6631</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>1.050</td>
<td>0.0816</td>
</tr>
<tr>
<td>N of observations</td>
<td>1213</td>
<td>1213</td>
</tr>
</tbody>
</table>

Notes: This table reports descriptive statistics for the measure of daily cross-sectional absolute deviation (CSAD) of individual stock returns with respect to the value-weighted market portfolio return and the market return ($r_m$) for Russian market during the period January 8, 2005 – December 31, 2009. In this case, the MICEX Index return is taken as a representative of the market return ($r_m$).

2 Winsorized results are qualitatively similar and are available upon request.
4.1 Regression results for the main test

The first set of results correspond to the return dispersion model (5), estimated for the Russian stock market for the whole sample period January 8, 2005 – December 31, 2009. The most important observation one can make from Table 2 is that cross-sectional return dispersion increases with the magnitude of the market return, an aspect that is consistent with standard asset pricing models. The significantly positive value of $\gamma_2$ indicates that the individual returns tend to diverge from the market returns over the period 2005-2009 (anti-herding).

According to this result, there is no evidence of herding behavior in the Russian stock market over the specified range. Apparently, the conclusion that herd behavior is more profound in emerging markets does not relate to the Russian stock market. Considering the fact that this method of measuring herding allows to detect herding based on stock returns, it is important to provide a deeper insight into the influences on these stock returns in this market. Before discussing these influences, attention is drawn to the asymmetric effects of the direction of the market movement on investor’s herd behavior.

Table 2 – Regression results for main test

| Main test: $\text{CSAD}_t = \alpha + \gamma_1|\text{rm}_t| + \gamma_2 \text{r}^2_{m,t} + \epsilon_t$ | $\text{Constant}$ | $|\text{rm}_t|$ | $\text{r}^2_{m,t}$ | $R^2$ adj. |
|------------------------------------------------|-----------------|-----------------|----------------|---------|
|                                                | 1.134 (0.000)   | 0.303 (0.000)   | 0.003 (0.004)  | 52.0%   |

Notes: This table reports the estimated coefficients for the dispersion-based regression model, concerning the value-weighted market portfolio: $\text{CSAD}_t = \alpha + \gamma_1|\text{rm}_t| + \gamma_2 \text{r}^2_{m,t} + \epsilon_t$. Here $\text{rm}_t$ and $\text{r}^2_{m,t}$ refer to the market return (index return) and squared market return at time $t$, respectively. The sample period is January 8, 2005 – December 31, 2009, yielding 1213 observations. Numbers in parentheses are p-values.

4.2 Regression results for different directions of the market movement

The first subtests performed were based on the belief that there is an asymmetric relationship between CSAD and market returns, distinguishing between rising and falling markets. Such an asymmetry is captured by regressing the dataset for selected cases, referring to either one of the two states of the market.
Table 3 – Regression results for negative market returns

<table>
<thead>
<tr>
<th>Test:</th>
<th>CSAD_{t}^{down} = α + γ_{1}^{\text{down}}l_{m,t}^{\text{down}} + γ_{2}^{\text{down}}(r_{m,t}^{\text{down}})^2 + ε_{t}</th>
<th>if ( r_{m,t} &lt; 0 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>\begin{align*}</td>
<td>\begin{align*}</td>
</tr>
<tr>
<td>1.116 (0.000)</td>
<td>0.323 (0.000)</td>
<td>-0.004 (0.071)</td>
</tr>
</tbody>
</table>

Notes: This table reports the estimated coefficients for the dispersion-based regression model, concerning the value-weighted market portfolio: CSAD_{t}^{down} = α + γ_{1}^{\text{down}}l_{m,t}^{\text{down}} + γ_{2}^{\text{down}}(r_{m,t}^{\text{down}})^2 + ε_{t}. Here \( γ_{2}^{\text{down}} \) refers to the coefficient of the value-weighted market portfolio return at time \( t \) when the market declines, and \( r_{m,t}^{\text{down}} \) refers to the value-weighted market portfolio return at time \( t \) when the market decreases. The sample period is January 8, 2005 – December 31, 2009, yielding 562 observations. Numbers in parentheses are p-values.

Table 3 reports the regression results for the relationship between CSAD and market returns during negative market returns (\( r_{m,t} < 0 \)) based on the value-weighted portfolio. When examining these regression results run with data restricted to down markets separately, a negative value of \( γ_{2}^{\text{down}} \) (significant at the 10%-level) indicates weak evidence of herding behavior during times of market losses. Therefore, the results suggest that herd behavior is more likely to be observed during periods of market losses. This is consistent with some of the behavioral finance literature in terms of the concept of loss aversion. According to this theory, investors’ utility function is shaped in such a way that investors have a greater tendency towards avoiding losses compared to acquiring gains (Kahneman & Tversky, 1991). Consequently, the finding that investors herd during periods of market losses can be due to investors’ intrinsic preference leading to asymmetric responses to market gains and losses.

Table 4 – Regression results for positive market returns

<table>
<thead>
<tr>
<th>Test:</th>
<th>CSAD_{t}^{up} = α + γ_{1}^{\text{up}}l_{m,t}^{\text{up}} + γ_{2}^{\text{up}}(r_{m,t}^{\text{up}})^2 + ε_{t}</th>
<th>if ( r_{m,t} \geq 0 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>\begin{align*}</td>
<td>\begin{align*}</td>
</tr>
<tr>
<td>1.076 (0.000)</td>
<td>0.357 (0.000)</td>
<td>0.003 (0.012)</td>
</tr>
</tbody>
</table>

Notes: This table reports the estimated coefficients for the dispersion-based regression model, concerning the value-weighted market portfolio: CSAD_{t}^{up} = α + γ_{1}^{\text{up}}l_{m,t}^{\text{up}} + γ_{2}^{\text{up}}(r_{m,t}^{\text{up}})^2 + ε_{t}. Here \( γ_{2}^{\text{up}} \) refers to the coefficient of the value-weighted market portfolio return at time \( t \) when the market inclines, and \( r_{m,t}^{\text{up}} \) refers to the value-weighted market portfolio return at time \( t \) when the market increases. The sample period is January 8, 2005 – December 31, 2009, yielding 651 observations. Numbers in parentheses are p-values.
Table 4 reports the regression results for the relationship between CSAD and market returns during positive market returns \( (r_m,t \geq 0) \) based on the value-weighted portfolio. Examining these regression results leads to a different conclusion than in the previous subtest, by showing no significant negative value of \( \gamma^U \). This provides further support for the theory of loss aversion, since individual returns tend to diverge from the market during positive market returns, while they tend to converge during negative market returns. Furthermore, one can observe that the statistical model of positive market returns is better in explaining the variability in the CSAD, compared to the statistical model of the negative market returns. This is the observation of comparing the adjusted R-squared values of both models, thus, highlighting the difference between 62.1% (Table 4) and 40.3% (Table 3).

4.3 Regression results for extreme market returns

After providing some support for the asymmetric effects of the market return on herd behavior, attention is drawn to the effect of extreme market returns on herd behavior. Both table 5 and 6 report no significant evidence in favor of herding behavior for the proposed cut-off areas (1%, 5%, and 10% respectively). These results are more significant for the extreme market returns in the upper tail compared to the ones in the lower tail.

However, from table 5, a decreasing value of \( \gamma \) is observed. This value will eventually conform to the result in table 3, when investigated at a higher cut-off area. the extreme market returns in the lower tail. Table 6, on the other hand, provides significant evidence against herding during extreme market returns in the upper tail. Thereby, it suggests that the individual returns tend to diverge from the market return over the period 2005-2009, showing behavior of anti-herding. Thus, it provides no significant evidence in favor of the statement that herd behavior is most likely to occur during periods of extreme market movements. Being so, it also lacks the evidence that investors are more triggered to follow the market consensus during such extreme times.
Table 5 – Regression results for extreme market returns test (lower tail)

<table>
<thead>
<tr>
<th>Test</th>
<th>CSAD(_{t \text{Down}}) = α + γ(<em>1)l(</em>{rm,t})*D(_t\text{L}) + γ(<em>2)r(</em>{m,j})(^2)*D(_t\text{L}) + ε(<em>t) if r(</em>{m,t}) &lt; 0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extreme down 1%</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>l(_{rm,j})*D(_t\text{L})</td>
</tr>
<tr>
<td></td>
<td>1.616 (0.000)</td>
</tr>
<tr>
<td>Extreme down 5%</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>l(_{rm,j})*D(_t\text{L})</td>
</tr>
<tr>
<td></td>
<td>1.504 (0.000)</td>
</tr>
<tr>
<td>Extreme down 10%</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>l(_{rm,j})*D(_t\text{L})</td>
</tr>
<tr>
<td></td>
<td>1.406 (0.000)</td>
</tr>
</tbody>
</table>

Notes: This table reports the estimated coefficients for the dispersion-based regression model, concerning the value-weighted market portfolio: CSAD\(_{t \text{Down}}\) = α + γ\(_1\)l\(_{rm,t}\)\*D\(_t\text{L}\) + γ\(_2\)r\(_{m,j}\)\(^2\)\*D\(_t\text{L}\) + ε\(_t\). The dummy variable D\(_t\text{L}\) indicates whether the market return on day t lies in the extreme lower tail of the distribution (D\(_t\text{L}\) equals 1 if this is the case, and is equal to zero otherwise). Three cut-off areas are used. The sample period is January 8, 2005 – December 31, 2009, yielding 562 observations. Numbers in parentheses are p-values.

Table 6 – Regression results for extreme market returns test (upper tail)

<table>
<thead>
<tr>
<th>Test</th>
<th>CSAD(_{t \text{Up}}) = α + γ(<em>1)l(</em>{rm,t})*D(_t\text{U}) + γ(<em>2)r(</em>{m,j})(^2)*D(_t\text{U}) + ε(<em>t) if r(</em>{m,t}) ≥ 0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extreme up 1%</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>l(_{rm,j})*D(_t\text{U})</td>
</tr>
<tr>
<td></td>
<td>1.659 (0.000)</td>
</tr>
<tr>
<td>Extreme up 5%</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>l(_{rm,j})*D(_t\text{U})</td>
</tr>
<tr>
<td></td>
<td>1.547 (0.000)</td>
</tr>
<tr>
<td>Extreme up 10%</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>l(_{rm,j})*D(_t\text{U})</td>
</tr>
<tr>
<td></td>
<td>1.461 (0.000)</td>
</tr>
</tbody>
</table>

Notes: This table reports the estimated coefficients for the dispersion-based regression model, concerning the value-weighted market portfolio: CSAD\(_{t \text{Up}}\) = α + γ\(_1\)l\(_{rm,t}\)\*D\(_t\text{U}\) + γ\(_2\)r\(_{m,j}\)\(^2\)\*D\(_t\text{U}\) + ε\(_t\). The dummy variable D\(_t\text{U}\) indicates whether the market return on day t lies in the extreme upper tail of the distribution (D\(_t\text{U}\) equals 1 if this is the case, and is equal to zero otherwise). Three cut-off areas are used. The sample period is January 8, 2005 – December 31, 2009, yielding 651 observations. Numbers in parentheses are p-values.
4.4 Regression results for the Russian financial crisis period

At last, the regression results for the Russian financial crisis period of 2008, compared to the preliminary period. As discussed, two versions of regressions were run to account for the effect of the Russian financial crisis of 2008 on the extent of herding behavior in the Russian stock market.

Table 7 – Results for Financial crisis period test

| Test: CSAD_t = α + γ_1 |r_m,t| + γ_2 r^2_{m,t} + ε_t |
|---|---|---|---|
| Before Russian financial crisis (for t = 01/08/2005 – 31/12/2007) |
| Constant | | | |
| 0.981 (0.000) | 0.320 (0.000) | -0.006 (0.220) | 30.2% |
| During Russian financial crisis (for t = 01/01/2008 – 31/12/2008) |
| Constant | | | |
| 1.435 (0.000) | 0.296 (0.000) | 0.003 (0.162) | 61.2% |

Notes: This table reports the estimated coefficients for the dispersion-based regression model, concerning the value-weighted market portfolio: CSAD_t = α + γ_1 |r_m,t| + γ_2 r^2_{m,t} + ε_t. Here r_m,t and r^2_{m,t} refer to the market return (index return) and squared market return at time t, respectively. The first test is based on the sample period January 8, 2005 to December 31 2007, yielding 732 observations. The second test is based on the sample period January 1, 2008 to December 31, 2008, yielding 234 observations. Numbers in parentheses are p-values.

When comparing the two regression in Table 7, one can observe that there is no significant value of γ_2 in either models. Furthermore, although not significant, the period before the Russian financial crisis indicates more evidence of herd behavior than the period during the crisis. Additionally, one can observe that the adjusted R-squared is significantly larger for the period during the crisis, compared to the period before. This implies that the statistical model accounts for 61.2% for the proportion of variability in the CSAD during the Russian financial crisis. This provides further evidence against herding, since the statistical model includes no significant negative value for γ_2.

This observation was partly explained by the absence of evidence in the models of extreme market returns, since periods of financial crisis are typically characterized by such abnormal returns. Evidently, the Russian financial crisis, which
followed from the Global Financial Crisis in 2008, did not trigger herding activity as the result of a contagion effect. That result must be interpreted with respect to the detection of herding based on the relationship between CSAD and the market return. For that reason, it is important to pay attention to the (other) influences on these stock returns in this market. These influences are argued when attempting to answer the problem statement in the next chapter.
CHAPTER 5 – SUMMARY AND CONCLUSIONS

Before attempting to answer the problem statement, the aspects that have been covered in this research are briefly discussed, so providing a summary of the recalled implications. In that way, an introduction is given to the general conclusion, after which the limitations are discussed.

5.1 Brief summary

This paper discussed the herding behavior in a financial setting, more specifically, the influences on the extent of such herding behavior by investors. Due to the scope of this research, it was chosen to limit the relationships with herding behavior down to the direction of the market movement, extreme market returns, and the Russian financial crisis. Prior to examining these relationships, literature was reviewed with respect to the types of herding, the measures of herding, and the importance of understanding herding behavior in stock markets. This was followed by the methodology, in which for each regression test it was explained how it was approached and how results should be interpreted in terms of the hypotheses. Consequently, the regression were run and analyzed, leading to the general conclusion.

5.2 General conclusion

In an attempt to answer the problem statement, the results are briefly discussed. First, over the whole dataset period, there was no evidence in favor of herding behavior in the Russian stock market. In fact, evidence suggested that the individual returns more tended to diverge from the market returns over the period 2005-2009, indicating anti-herding behavior. Second, there was evidence that supported the statement of the asymmetric behavior of investors’ herding in the Russian stock market. Being so, it was consistent with the theory of loss aversion. Third, no significant evidence was found in favor of the statement that herd behavior is most likely to occur during periods of extreme market movements. Being so, it lacks the evidence that investors are more triggerd to follow the market consensus during such extreme times. At last, no evidence was found for herding behavior during the Russian financial crisis, which followed from the Global Financial Crisis in 2008. Apparently, the Russian stock
market did not trigger herding activity as the result of a contagion effect during these times.

When combining these outcomes, it becomes clear that herding behavior is not present in the Russian stock market for the period January 2005 – December 2009, at least not with respect to the applied methods. While one can argue that the Russian financial market is simply too developed to show this kind of behavior, one must also consider the other influences.

There are only a few empirical studies discussing other influences on Russian stock market returns, but this does not imply the absence of significant results. Ivanter and Peresetsky (2000) concluded from analyzing daily market data for the period May 1996 – October 1997 the increasing integration of Russian and international financial markets. In addition, Jalolov and Miyakoshi (2005) concluded for the period May 1995 – March 2003 that German markets are a good predictor for Russian stock market returns, due to the close German relations in trade and investment with Russia. Besides the influence of the US stock market, Hayo and Kutan (2005) also found evidence for the predicting value of oil prices.

Peresetsky (2011) concluded this research with the finding that the US market index (S&P500) has some predictive power for the Russian market index with the exception of the highly volatile period during the 2008 crisis. This can explain why the contagion effect of the Global Financial Crisis, which started in the US, was not substantial. So, while crisis possibly triggered herding in the country of origin, the US, the weaker contagion effect caused no significant trigger of herding activity in the Russian market.

At last, empirical studies indicated the influence of political as well as economic news on the Russian financial market. While some abnormal endogenous shocks were related to those influences, others were not. Peresetsky (2011) provided further support for the statement of structural instability of the Russian financial market by Anatolyev (2008).

What we can conclude from these findings is that there are many other factors that cause Russian stock market returns to move into a specific direction. So, even when herding was present during the investigated period, this effect may be diminished by the other influences on the stock market. This has further implications for the limitations of this research.
5.3 Limitations and recommendations

Due to the scope of the research, it is limited for the following reasons. First, the other influences on the Russian financial market were not incorporated in the model. More specifically, by incorporating the indexes of the US and/or German markets into the model, more solid conclusions can be drawn. Second, the research has limited itself to the investigation of asymmetric effects of the direction of the market movement. However, other researches also included the investigation of these effects with respect to trading volume and market volatility. It would be interesting to analyze these regressions to provide further support for asymmetric behavior. Third, the CSAD model restricts itself to detecting herding with respect to market returns. Therefore, it does not indicate who causes this herd behavior, so, it does not distinguish between individual and institutional investors. At last, this research was based on the MICEX Index, including the 30 most major Russian stocks. Empirically comparing the relationship between CSAD and the market return for large stock with small stocks would be of significant interest.

To conclude, it would be interesting to see how results change when the discussed limitations were included in future researches.

5.4 Acknowledgements

Special thanks goes out to E.S. Pikulina (Supervisor) for her useful comments and suggestions.
CHAPTER 6 – REFERENCES


