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HERD BEHAVIOR ON BORSA ISTANBUL (BIST): AN EMPIRICAL ANALYSIS

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ABSTRACT

Doctoral Thesis

Doctor of Philosophy (PhD)

Herd Behavior on Borsa Istanbul (BIST): An Empirical Analysis

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Behavioral finance is a field that has grown toward the end of 20th century as a reaction to the efficient market hypothesis. This new field studies the effect of investor psychology on financial decisions and explains stock market anomalies in financial markets. Herding is such an anomaly that is defined as mimicking others' decisions or market trend.

The aim of the study is to detect whether there is herding or not in Borsa Istanbul. To test the existence of herding, stock returns traded on Borsa Istanbul and BIST 100 Index as market indicator are used. Data covers daily returns from 1988 to 2014 and intraday returns from 1995 to 2014. Firstly, herding is analyzed based on the methodology of cross-sectional dispersion of the stocks developed by Christie and Huang (1995) and Chang, Cheng and Khorana (2000). The results indicate that there is no herding for both up and down markets for daily and intraday intervals in Borsa Istanbul. However, tendency of herding is higher in up markets.

To enhance and compare the results, the methodology based on the cross-sectional volatility of beta coefficients suggested by Hwang and Salmon (2004) is used. This methodology has provided evidence of herding in Borsa Istanbul. It is also observed that investors follow the market trend more in session two markets rather than session one markets. Thus, it is concluded that investors imitate the others more under normal market conditions rather than noisy market

conditions. These results are consistent with the assumptions of Hwang and Salmon (2004).

Keywords: Behavioral Finance, Herd Behavior, Borsa Istanbul, Cross-Sectional Dispersion.

ÖZET

Doktora Tezi

Borsa İstanbul (BIST)' da Sürü Davranışı: Ampirik Bir Analiz

Hilal Hümeyra ÖZSU

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Davranışsal finans, 20. yüzyılın sonlarına doğru etkin piyasa hipotezine tepki olarak ortaya çıkan bir alandır. Yatırımcı psikolojisinin finansal kararlar üzerindeki etkisini araştırmakta ve hisse senedi piyasalarında görülen anomalileri açıklamaktadır. Sürü davranışı yatırımcıların, diğer yatırımcı kararlarını ya da piyasa eğilimini takip etmeleri olarak tanımlanan bir anomalidir.

Bu çalışmanın amacı, Borsa İstanbul'da sürü davranışı olup olmadığını belirlemektir. Sürü davranışının varlığını test etmek için, Borsa Istanbul'da işlem gören hisse senetleri ve piyasa göstergesi olarak BIST 100 endeksi kullanılmıştır. Veri seti 1988 ve 2014 yılları arasındaki günlük getirileri ve 1995 ve 2014 arası gün içi getirilerini kapsamaktadır. İlk olarak, sürü davranışı Christie ve Huang (1995) ve Chang, Cheng ve Khorana (2000) tarafından geliştirilen hisse senedi getirilerinin yatay kesit değişkenliğine dayalı yöntem kullanılarak analiz edilmiştir. Araştırmanın sonuçları Borsa Istanbul'da günlük ve gün içi verileri için yükselen ve alçalan piyasalarda sürü davranışı olmadığını göstermektedir. Ancak, yükselen piyasalarda sürü davranışı eğilimi daha yüksektir.

Araştırmanın sonuçlarını genişletmek ve karşılaştırma yapabilmek için Hwang ve Salmon (2004) tarafından geliştirilen beta katsayılarının yatay kesit değişkenliğine dayalı yöntem kullanılmıştır. Buna göre, Borsa Istanbul'da sürü davranışı gözlemlenmiştir. Ayrıca yatırımcıların birinci seans piyasasına göre ikinci seansda pazar trendini daha çok takip ettikleri gözlemlenmiştir. Bu sebeple, yatırımcıların diğer yatırımcıları değişken piyasa koşullarından ziyade

normal piyasa koşularında daha çok takip ettikleri görülmüştür. Bu sonuçlar Hwang ve Salmon (2004)'ın varsayımları ile uyuşmaktadır.

Anahtar Kelimeler: Davranışsal Finans, Sürü Davranışı, Borsa İstanbul, Yatay Kesit Değişkenliği.

HERD BEHAVIOR ON BORSA ISTANBUL (BIST):
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ABBREVIATIONS

BIST	Borsa Istanbul
CSSD	Cross Sectional Standard Deviation of Stock Returns
CSAD	Cross Sectional Absolute Deviation of Stock Returns
CAPM	Capital Asset Pricing Model
LSV	Lakonishok, Shleifer and Vishny
US	United States of America
PIGS	Portugal, Italy, Greece, Spain
AR(1)	Autoregressive(1)
SMB	Small Minus Big
HML	High Minus Low
GDP	Gross Domestic Product
MERVAL	Argentina's Main Market Index

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INTRODUCTION

Fama (1965) has developed efficient market hypothesis and argued that investors make decisions in a rational way to hold an optimal portfolio and maximize their returns at a given level of risk. Accordingly, market is efficient and investors have all available information which is reflected in prices. Thus, the market as a whole does not deviate from rationality. Contrary to this traditional approach to finance, behavioral finance states that investors are affected by their emotions during their judgment and decision making process under uncertainty and risk. Numerous researchers have emphasized the existence of unexpected results called as the anomalies in financial markets, indicating market inefficiency during the past two decades.

Herd behavior is one of the anomalies which is defined in the finance literature as mimicking the other investors' decisions. The investors trade in the same directions with the other investors rather than acting based on their own beliefs. Barber and Odean (2007) point out that investors select to buy the stock which attracts the others' attention at most. However, investors do not always follow the others to herd. They make similar decisions because of accessing the same information and interpreting this information similarly, which is called spurious herding. In case of intentional herding, investors should decide to follow the consensus after observing the others' behaviors. There are some forces leading to herd behavior such as information, reputation and compensation.

Researchers have analyzed herd behavior by using different measurement methods. The widely used methods are cross-sectional dispersion of stock returns, cross-sectional volatility of beta coefficients and Lakonishok, Shleifer and Vishny (LSV) measure in the literature. In this study, firstly, the methodology of cross-sectional dispersion of the stock returns suggested by Christie and Huang (1995) and developed by Chang, Cheng and Khorana (2000) are applied. They have investigated whether dispersions of stock returns decrease during periods of large price movements. Small dispersions between stock returns and market return are expected during these periods if there is herd behavior. Then, the presence of herding is tested by using the methodology based on cross-sectional volatility of the beta coefficients. This model suggested by Hwang and Salmon (2004) provides to examine herd behavior under not only noisy market conditions but also normal market conditions. Moreover, the model enables to analyze herding by including macroeconomic fundamentals such as market volatility, market return, size and value factors. This also provides opportunity to differentiate intentional and spurious herding and to evaluate changes in herding levels.

This study aims to investigate the existence of herd behavior in Borsa Istanbul. The data ranges from 1988 to 2014 for daily returns and ranges from 1995 to 2014 for intraday returns. Daily and intraday intervals used in this study provide to compare the results of session one and session two markets. Furthermore, this is the first comprehensive attempt which takes into account several factors such as market volatility, market return, size and value factors to detect herd behavior in Borsa Istanbul. This study also contributes to the international literature in the field of behavioral finance by measuring similar variables that were used in the earlier studies and strengthening their theoretical and empirical frameworks[1].

The study consists of four chapters. In the first chapter, the emergence and development of behavioral finance is presented and then theoretical basis of the behavioral finance and herd behavior is explained. The second chapter provides literature review and detailed explanation for the measurement methods of herd behavior. In the third chapter, the purpose of the study and hypotheses are explained, the data is described, and descriptive statistics are reported. In the last chapter, empirical findings of the study are presented and discussed. The contribution and the limitations of the study and the suggestions for further research are provided in the conclusion part.

[1] In international literature, earlier studies analyzed herding based on size and book-to-market ratio (Wang, 2008; Hassairi and Viviani, 2011), market volatility and market return (Pop, 2012). In Turkey, Altay (2008) investigated herding by using the CAPM approach excluding market volatility, market return, size and book-to-market ratio.

CHAPTER ONE
BEHAVIORAL FINANCE AND HERD BEHAVIOR

In this chapter, at first, efficient market hypothesis and then the emergence and development of behavioral finance is presented. At last, theoretical basis of the behavioral finance and types of herd behavior are explained.

1.1. EFFICIENT MARKET HYPOTHESIS

In 1900, Louis Bachelier, in his article which was accepted as the first concerned with the market efficiency, has investigated the fluctuations of stock prices on the basis of the probability theory. The probability theory is consistent with the analysis of random events which was used and developed as a theory in Fama (1965)’s and Paul Samuelson (1965)’s articles. Random walk theory assumes that stocks prices change and deviate randomly from past prices, and thus, they cannot be predicted easily (Malkiel, 2003: 59).

Consistent with the random walk theory, Fama (1970) has suggested the efficient market hypothesis (EMH), which was widely accepted in finance literature, and has stated that stock markets are efficient. In his article, efficient market is defined as “a market in which prices always fully reflect available information” (Fama, 1970: 383) and in this efficient market, rational investors actively trade by trying to predict future performance of stocks to maximize their profits (Fama, 1965: 3-4). Investors estimate the intrinsic value and compare it with the market value to estimate the future price of the stocks. However, Shleifer (2000), Ehrhardt and Brigham (2010) and Brigham and Daves (2012), in their book, has stated that the stock price must converge to the intrinsic value of the stocks under the efficient market conditions because of either the rational investors or the arbitragers’ buy and sell actions of under or overpriced stocks. If stock price diverges from its intrinsic value, investors buy undervalued stocks and sell overvalued stocks to take advantage of this mispricing in the financial market (Yalcin, 2010: 26). However, competition among investors drive prices to their intrinsic values due to the non-existence of arbitrage opportunities in efficient markets (Malkiel, 2003: 2; Brigham and Ehrhardt, 2010: 292; Herschberg, 2012: 9). Thus, it is not possible to make superior profits in efficient markets.

Fama (1970) divides market efficiency into three forms, called as weak form, semi-strong form and strong form efficiency. The validity of these three forms have been investigated and tested in different financial markets.

Weak form efficiency is basically consistent with the past prices of the stocks. Bodie, Kane and Marcus (2009) state that stock prices reflect all information that can be derived by examining the history of past prices. However, it is difficult to estimate future prices by observing the past prices because of the random changes of prices. To measure weak form efficiency, serial correlation tests, runs (or signs) tests and testing of trading rules are commonly used by technical analysts. To have abnormal returns is not possible by using the technical analysis which forecasts future price movements on the basis of the past price movements. Future prices can be affected by new and unpredictable information that emerges today hence it is based on surprise information rather than past prices of the stocks (Ali and Mustafa, 2001: 651). However, it is possible to beat the market and make superior profits by using the fundamental analysis or insider trading in the weak form of market efficiency (Yalcin, 2010: 27).

Semi-strong form of efficiency states that it is not possible to have abnormal returns by using fundamental analysis which is analyzing publicly available information. This information such as fundamental data on the firm's product line, quality of management, balance sheet composition, patents held, earning forecasts, and accounting practices in addition to past prices is analyzed by event (or announcement) studies (Bodie, Kane Marcus, 2009: 348-349). Under the semi-strong form efficiency conditions, the stock prices reflect such information that prevents the abnormal returns. However, making superior profits is possible for insider traders in semi-strong form of efficiency (Yalcin, 2010: 28).

Strong form efficiency holds that the prices fully reflect publicly available and private information and investors cannot have abnormal returns even if they have insider information in addition to the past prices and the publicly available information (Fama, 1970; Coban, 2009). Strong form efficiency is "based on the assumption that the institutions issuing recommendations have access to information inaccessible to the community of investors" (Potocki and Swist, 2012: 155). The presence of strong form efficiency on the market implies that it is impossible to achieve above-average profits when having a monopolistic access to a full set of information (Potocki and Swist, 2012: 156).

Shleifer and Summers (1990: 19-20) suggest a different approach to the efficient market hypothesis that investors are not fully rational and they are affected by their beliefs or sentiments during decision making under uncertainty. Furthermore, they point out the existence of risky and limited arbitrage conditions. Black (1986: 529-531) has used the word "noise" to define irrationality. Accordingly, noise is contrasted with information. It makes observations imperfect and prevents investors to predict expected return of the stock correctly. Thus, if people, who trade on noise rather than information, expect to make profits, they are incorrect. Most of the time, they will lose money by trading, while the information traders will make money. Under the noisy market conditions, mispricing will become more extreme and arbitrageurs will not be able to exploit the mispricing to drive prices to their fundamental values. Investors, even if they know that the stock is not priced correctly, may not be able to make profit from an arbitrage opportunity because of the possibility of noise traders' irrational investing activities (Yalcin, 2010: 29: Herschberg, 2012: 18). Behavioral finance has started as a response to traditional finance because of these irrational investing activities.

1.2.BEHAVIORAL FINANCE AND HERDING

The traditional finance assumes that people behave rationally leading to efficient markets, but they do not (Barber and Odean, 1999). Toward the end of the 20^{th} century, this theory was challenged in several ways. In the 1980s, the Japanese stock price and land price bubble in which stock prices and land prices of Japanese corporations grew dramatically from 1986 to 1988 and declined dramatically from 1989 to 1992 (Stone and Ziemba, 1993: 149). A severe and unexpected decline in stock prices also occurred in 1987 (Carlson, 2006: 1). As similar, a rapid economic crash came in Taiwan Stock Market in early 1990 (Chen, 2001: 215).

There have been a number of large market events and large deviations from the theoretical relation that cast doubt on the basic assumptions of efficient market hypothesis (Ritter, 2003: 9). Economists could not have fully explained these market events in a rational way. They have emphasized that the dramatic drops in market prices, which occurred in the 1980s, can only be explained by psychological factors, as the fundamental elements of the economy do not change rapidly over that period (Malkiel, 2003: 73-74). Montier (2002) suggests that market efficiency is perhaps not the best paradigm for thinking about real world financial situations. Hence the foundations of corporate finance need to be rebuild from a behavioral standpoint. Behavioral finance is a new approach to financial markets that has developed as a reaction to these unexpected events (Barberis and Thaler, 2003: 1053).

Behavioral finance basically studies the effect of investor or manager psychology on their financial decisions by using models which analyze irrational agents, either because of preferences or mistaken beliefs (Ritter, 2003: 2). It concerns with the effects of psychology on corporate finance including managerial decisions. In recent years, scholars from a variety of social science disciplines focus more on how managers make decisions. Thus, managerial decisions have been studied in terms of several psychological anomalies in decision making researches (Scholz, 1983: 4).

Behavioral finance is based on two building blocks. First one is limits to arbitrage which argues that it may not be possible to make profit from market dislocations for arbitrageurs because of the irrational investors trading in the market. Second one is cognitive psychology which focuses on how people think (Thaler and Barberis, 2002: 36; Ritter, 2003: 1; Herschberg, 2012: 8).

Researchers have investigated investors' decisions in terms of many psychological biases (Ritter, 2003: 3). First of all, investors all tend to be more optimistic about the future and they believe that they can control the outcomes (Thaler, 2001; Heaton, 2002). Optimism leads to investors to overvalue the firm with the high investment levels (Heaton, 2002: 35; Hirshleifer, et al., 2004: 13; Shefrin, 2001: 14). In a related phenomenon, investors believe they are better forecasters than they really are (Thaler, 2001). They are overconfident about their abilities and the future. Because of their overconfidence, they have optimistic expectations and thus, their preferences may also create distortions (Ritter, 2003: 2). For instance, they may underestimate the probability of default, and as a result choose an overly debt-heavy capital structure (Shefrin, 2001: 10).

Framing is the concept how the problem is presented to individuals (Ritter, 2003: 4). Decision making literature has indicated that individuals give different answers to the same decision problem if the problem is exhibited in a different format. This decision process is called as a framing effect (Tversky and Kahneman, 1981 & 1986). When the same situation is presented differently to individuals, they select a different alternative. Their decisions can change based on how the problem is framed. For instance, their choices will be different when they are faced with the problems which are framed positively by comparison to the ones framed negatively, even if the result is the same. The ‘‘Asian disease problem’’ described by Tversky and Kahneman (1981) is the most common example of the framing effect. In their study, "decision makers were asked to choose between a certain or a risky option to save lives as a positive frame or minimize deaths as a negative frame from an unusual disease" (Gonzalez et al., 2005: 2). They found that investors tend to avoid (take) risk when they evaluate the profits (losses).

During the last 30 years, numerous researchers have studied the framing effect by using different problem sets. Kahneman and Tversky (1979) have developed the prospect theory to explain framing effect. Thaler (2001) also suggests prospect theory to understand human cognition during decision making process.

Prospect theory is important for decision making under uncertainty. It varies from the expected utility hypothesis in important ways. The traditional finance theory states that investors make decisions to provide maximum expected utility of wealth when faced with uncertainty. This approach is a rational-based framework (Han & Hsu, 2004). However, in reality, it is perceived that investors do not usually act rationally. Investors do not display rational behavior under risk. That is, investor behavior is better explained by prospect theory (Durukan, 1999) which is a theory of decision making under risky conditions. Prospect theory says that people avoid risk in the domain of gains and take risk in the domain of losses (McDermott, 1998: 29). It directly relates to the framing of problem sets and evaluation of decision making process.

Kahneman & Miller (1986) and Kahneman & Tversky (1979) highlight the reference point which is the keystone of prospect theory. Framing effect is explained in the way of gains and losses based on the reference point. The theory assumes that while the outcome of decision alternative, which is above the reference point, indicates gain, the outcome which is below that point indicates loss. Prospect Theory argues that investors usually avoid risk when choosing between the alternatives which are framed as gains, and take risk for alternatives which are framed as losses (Fischhoff, 1983; Sullivan, 1997; Thaler, 2000).

Herding, which is another notion related to cognitive psychology, is referred to as “everyone doing what everyone else is doing, even when their private information suggests doing something quite different” (Banerjee, 1992: 798). In financial markets, it is referred to buying (selling) the same stocks that the others buy (sell) (Zhou and Lai, 2009: 389). Scharfstein and Stein (1990: 465) examine some of the forces that can cause herd behavior in investment decisions. Devenow and Welch (1996) have divided these forces into three types which are information-based, reputational-based, and compensation-based herding.

1.3. THEORIES OF HERDING

Herding is a hot topic that has been widely studied in the behavioral finance literature over the past decade. In the case of herding, investors suppress their own information and beliefs, and decide based on actions of other investors, who trade in the market, even if they disagree with their predictions (Christie and Huang, 1995: 31). Nofsinger and Sias (1999: 2263) also define herding as "a group of investors trading in the same direction over a period of time". That is, they face similar decision alternatives, have similar information sets and thus, they imitate each other randomly.

There have been recently attempts to explain the reasons behind herding. The notion of similarity alone is insufficient. It may be due to various reasons and not all of them may be irrational (Frömmel, 2013: 427). Herding may emerge as a result of not only irrational but also rational investor behavior.

1.3.1. Rational Herding

Herding is not directly an indicator of irrational behavior. Individuals can alter their behavior and act in a similar way with the others due to rational reasons (Oehler and Chao, 2000: 3-4). Such herding may occur randomly, or individuals interpret information similarly because they have access to the same information. Alternatively, pioneered in Banerjee (1992) and Bikchandani, Hirshleifer and Welch (1992), such herding occurs where people observe the collective actions of the market, derive information from them and then, disregarding their own information, follow the market trend (Park and Sgroi, 2009: 1).

Scharfstein and Stein (1990), DeLong, Shleifer, Summers and Waldman (1990), Banerjee (1992), Rajan (1994) and Bikhchandani and Sharma (2001) have studied rational view of herding. Although it is difficult to distinguish, Bikchandani and Sharma (2001) divided rational herding into two types; spurious herding and intentional herding.

1.3.1.1. Spurious Herding

Bichchandani and Sharma (2001: 281) defines herding as investors imitating the behavior of other investors. However, "spurious" herd behavior should be differentiated from "intentional herding" where investors facing similar decision choices and information sets make similar decisions. For instance, when interest rates increase, investors act in the same way as a reaction to this commonly known public information. This is not consistent with the definition of herding, because investors do not alter their decisions after observing others, instead they make decisions in the same way because of changes in interest rates.

Zhou and Lai (2009: 388) are the first to show that the stock market is efficient even if there is herding. By empirically separating herding into "spurious herding" and "intentional herding", they find that investors herd because they are equally informed, and they make decisions for the purpose of investing rather than simply doing what others do.

Zhou and Lai (2009) have claimed that when the increase in stock price reflects the fundamental price, investors whether they are informed or uninformed may buy the stock. The issue is to separate informed investors from uninformed ones to know whether herding is spurious or intentional.

“Spurious herding”, known as “unintentional herding” in Lakonishok et al. (1992), is referred to all investors reacting identically to the same piece of news. Spurious herding may reflect either the reaction of investors to commonly known public information or different opportunity sets faced by investors. Particularly in crisis periods, investors acting as a herd may only reflect their perception of identical fundamental information of firms (Zhou and Lai, 2009: 391).

If investors herd “spuriously” because they are equally informed, the stock market is said to be efficient (Zhou and Lai, 2009: 391). Because spurious herding is therefore no herding in spirit of definition above, even though investors act the same, they do not imitate each other (Frömmel, 2013: 429). For investors to herd in reality, they must change their decisions after observing the others' behaviors. If investors would have made an investment without knowing others' decisions and decide not to make this investment, or besides if they alter their decisions from not investing to making the investment after gathering information, it can be said that investors herd (Bikhchandani and Sharma, 2001: 280).

As stated earlier, spurious herding occurs when a group of investors make similar decisions because they face similar information sets (Christofersen and Tang, 2009: 11). Hence, an intentional element has to be taken into account to evaluate herding better (Oehler and Chao, 2000: 3-4).

1.3.1.2. Intentional Herding

The issue is to separate informed investors from uninformed ones to know whether herding is spurious or intentional. Intentional herding based on the behavior of others is a rational decision when other investors are better informed (Blasco , Corredor and Ferreruela, 2009: 4). This type of herding itself can again be linked to several potential reasons leading to information-based herding, reputation-based herding and compensation-based herding (Frömmel, 2013: 429). That is, investors’ reputation, compensation payoffs and their peers’ information are most basic motivations for them to herd intentionally (Gavriilidis et. al. 2013: 193).

1.3.1.2.1. Information-Based Herding

One of the causes of herding is that investors face similar decision choices, that is, they have similar information sets, face similar action choices, and face similar payoffs. As a result, they make similar decisions (Kandir, 2006: 21). In this situation, investors communicate with each other or observe the other investors′ behavior. Then, the better alternative between choices is determined by using direct analysis or relying on the information of others. Nevertheless, to make an analysis can be costly and time-consuming, thus, to choose the latter can be more reasonable (Bikhchandani, Hirshleifer and Welch, 1998: 152). For instance, it is possible that fund managers follow the others to reap informational payoffs. Furthermore, an investor may follow the others, because he believes that they have better information or better skills to process information (Gavriilidis, Kallinterakis and Ferreira, 2013: 193).

If individuals have some information about the actions of other investors, then inferences about an investor′s private information can be made from the actions chosen. Thus, these first investors determine the type of behavior on which individuals herd (Bikhchandani and Sharma, 2001: 284). Individuals prefer to imitate the behavior of his predecessors without regard to his private signal, even though he would have chosen differently if he has acted on his own information alone.

1.3.1.2.2. Reputation-Based Herding

Intentional herding can be perceived as taking an action that is common to others and "sharing the blame" so as to avoid being alone as a result of a bad consequence, especially when information is very scarce (Zhou and Lai, 2006: 391).

Reputation arises because of discredit or uncertainty about the ability or skill of the manager. If an investment manager does not have confidence on his own ability to trade on the right stocks or to manage the portfolio, making similar decisions with other professional managers provides an advantage. Even if they do not make the right decision, their reputation is preserved because of the herding activity (Bikhchandani and Sharma, 2001: 291). As stated in the study of Scharfstein and Stein (1990) principals compare the investment performance of agents with the others. Thus, the diffident agent about his abilities may follow the actions of others due to their reputations. However, that causes an incorrect assessment of the manager's performance. Since it cannot be possible to determine if his performance is due to his skills or herding acitivity. (Gavriilidis et al., 2013: 193; Frenkel, Hommel and Rudolf, 2005: 621-624). It can be concluded that a "compensation-reputation scheme rewarding imitation" is observed between the managers. Because their compensation depends on their performance in comparison with others' performance (Blasco and Ferreruela, 2008: 72).

The risk of the mimicking the others because of reputation concerns may also affect the reputation negatively. If the investment decision of the others is not profitable, the manager may face with losses because of his herding activity, even if he knew the correct decision. On the other hand, if the manager does not herd and act relying on his own information, a big negative impact may occur on the manager's career in case of failure (Lütje and Menkhoff, 2005: 788; Frenkel, Hommel and Rudolf, 2005: 787).

Döm (2003) and Scharfstein and Stein (1990) divide investment manager types into two categories; smart and dumb managers. Dumb managers act without attracting the people's attention and follow the smart managers. Because, if they refuse the smart managers' information and decide based on their own information in a wrong way, they lose their reputation in case of failure.

1.3.1.2.3. Compensation-Based Herding

The emergence of compensation-based herd behavior can be explained by agency theory. Managers (agents) are able to make decisions on behalf of the shareholder (principal) and they have some incentives to generate high values and to maximize a weighted average of expected profits (Scharfstein and Stein, 1990: 469-470). If an investment manager's performance is compared with the performance of the other managers and his compensation depends on the result of this comparison, then this distorts the manager's incentives and he turns out with an inefficient portfolio. It may also cause herd behavior (Bikhchandani and Sharma, 2001: 292).

Massa and Patgiri (2007: 3) have studied the relation between herding, risk taking and managerial incentives. It is found that managers take risk and herd less in the case of high incentives. They show higher performance due to high incentives, since managers' payoff depends on his performance. By taking more risk, they turn to their fundamentals and decide based on their own information. They avoid mimicking the others. Thus, if managers care about their reputation, they will follow the consensus. However, if they care about payoff and incentives, they will have to trade off the loss of reputation against incentives. As the profit due to high incentives and increased effort of managers increases, herding level decreases (Scharfstein and Stein, 1990: 475-476).

1.3.2. Irrational Herding

Chang, et. al. (2000: 1652) states that a herd arises when investors tend to imitate each other without disregard to their own beliefs. This behavior can be explained by either rational forces as stated earlier or investor psychology which is associated with the social pressure. Social pressure affects the investment decisions of the agents and keep them from decision making based on their own judgment (Döm, 2003, Kucuksille, 2004, Coban, 2009).

A social psychologist Asch (1955) claimed that people herd because of social pressure or group pressure. He has conducted an experiment to investigate social pressure and conformity to the majority. Seven confederates and then "real" participants are placed in a classroom. Confederates are aware of the experiment but the real participants are not. It was said to real participants that this is an experiment on visual judgment. At first, a white card with a single black line is shown to the confederates and participants. Then, the second card with three lines are given to them and are asked to make comments about lengths of the lines and to choose the line which matches the single black line on the first card in length. It is necessary to say their answers one at a time. The real participants are sat towards the end of the table to direct them to answer last. It is asked from the confederates to give the same incorrect answers. The aim of the experiment is to observe the reaction of each real participant to the confederates' behavior. It is investigated that whether real participants decide based on their own information and act differently from the confederates or reject their correct information and conform to the majority.

After the experiment, an interview has also been conducted with each real participant separately. Although most of the participants choose the correct line with the same length during interview, they respond incorrectly in the same way as the confederates during the experiment due to the group pressure. Additionally, most of the real participants have given explanations on their answers during interview and said that they did not really believe their conforming answers, but give the same answers with the group for fear of being ridiculed or thought peculiar. A few of them said that they really did believe the group's answers were correct. As a result, people conform to the majority group estimates for two main reasons. They believe their own private information is not correct and the group has better information or they conform to avoid being different even if they believe the group is not correct and they follow the majority of the group (Asch, 1955: 31-35).

CHAPTER TWO
HERDING MEASUREMENTS

Numerous researches have focused on the herd behavior in different stock markets. Three methodologies are widely used to examine the herd behavior in the literature. One of them is cross sectional dispersion of stock returns suggested by Christie and Huang (1995) and developed by Chang et al. (2000). The other one is the cross-sectional volatility of beta coefficients suggested by Hwang and Salmon (2001, 2004). The third method developed by Laconishok, Shleifer and Vishny (1992) has suggests using the number of shares which investors hold rather than stock returns to detect herd behavior.

2.1. CROSS-SECTIONAL DISPERSION OF STOCKS RETURNS

Christie and Huang (1995) are the first researchers to develop and use the cross-sectional standard deviations of stock returns. Christie and Huang (1995: 32) state that investors mostly tend to act without disregard to their own beliefs, and thus, herding arises during periods of market stress. They have investigated whether dispersions of stock returns decrease during periods of large price movements in US stock markets. Large dispersions between stock returns and market return are not expected during these periods if there is a presence of herding. They have analyzed daily returns from July 1962 to December 1988, and monthly returns from December 1925 to December 1988. As a result of the analysis, their findings pointed out that dispersions of stock returns increase during periods of market stress implying that herd behavior has not been observed. Hwang and Salmon (2004: 587) argued that this may be due to investors basing their decisions on fundamentals rather than other investors' behavior at times of crisis.

Chang, Cheng and Khorana (2000) have extended the model developed by Christie and Huang (1995) and proposed the cross sectional absolute valuation of stock returns. They have investigated the herd behavior of investors in the United States (US), Hong Kong, Japan, South Korea and Taiwan by using daily stock returns. They have examined that not only decreasing but also non-linear relation is expected between dispersion of stock returns and market return to detect herd behavior. Their results indicate that dispersions of stock returns tend to increase implying that the returns do not herd around the market return during periods of large price movements in developed markets such as the United States (US), Hong Kong and Japan. On the contrary, smaller dispersions of stock returns have been found hence providing herd behavior in South Korea and Taiwan.

2.1.1. Methodology

As stated earlier, the methodologies based on cross-sectional dispersion of stock returns are divided into two models: cross-sectional standard deviation of the stocks and cross-sectional absolute valuation of the stocks.

2.1.1.1. Methodology of Cross-Sectional Standard Deviation of the Stock Returns

Christie and Huang (1995) analyzed the dispersions of stock returns during periods of large price movements to examine herd behavior. The dispersion is formulated by equation (1):

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

where *CSSD* is the cross-sectional standard deviation of stock returns, *N* is the number of firms in the portfolio, $R_{i,t}$ is the observed stock return of firm *i* at time *t*, $R_{m,t}$ is the cross-sectional average of *N* returns in the portfolio at time *t*. They have used dummy variables and suggested the following regression equation (2) to differentiate between the return dispersions in up and down markets.

$$CSSD_t = a + \beta^D D^D{}_t + \beta^U D^U{}_t + \epsilon_t \qquad (2)$$

where $D^D{}_t$ is equal to one if the market return on day t lies below the 1 % and 5 % of the return distribution and equal to zero otherwise, $D^U{}_t$ is equal to one if the market return on day t lies above the 1 % and 5 % of the return distribution and equal to zero otherwise. Small dispersions between stock returns and market return are expected during extreme lower and upper market movements to examine the presence of herding. Negative and statistically significant coefficients of β^L and β^U are indicators of small dispersions hence resulting herding behavior. In other words, in the presence of herding, stock returns do not diverge from the overall market return. Furthermore, if which coefficient is lower (β^L or β^U) in contrast with the other, then, tendency of herding is higher, as stated in Christie and Huang (1995).

2.1.1.2. Methodology of Cross-Sectional Absolute Valuation of the Stock Returns

Chang, Cheng and Khorana (2000) have extended the model suggested by Christie and Huang (1995) and conducted the methodology of cross-sectional absolute deviation of the stocks (CSAD) to measure dispersions of stock returns which is expressed by equation (3) as:

$$CSAD_t = \frac{\sum_{t=1}^{N} |R_{i,t} - R_{m,t}|}{N} \qquad (3)$$

where *CSAD* is the cross-sectional absolute deviation of stock returns, *N* is the numbers of firms in the portfolio, $R_{i,t}$ is the observed stock return of firm *i* at time *t*, $R_{m,t}$ is the cross-sectional average of *N* returns in the portfolio at time *t*. They have used a quadratic equation, to investigate the presence of herd behavior.

$$CSAD_t = a + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 \qquad (4)$$

where $R_{m,t}$ is the average market return of the sample, at time *t*. The negative and statistically significant γ_2 coefficient indicates herd behavior.

Chang, Cheng and Khorana (2000) also proposed a comprehensive regression analysis to capture the non-linear relation between stock dispersions and market return by the following equation:

$$CSAD_t^{DOWN} = a + \gamma_1^{DOWN} |R_{mt}^{DOWN}| + \gamma_2^{DOWN} (R_{mt}^{DOWN})^2 + \epsilon_t \qquad (5)$$

$$CSAD_t^{UP} = a + \gamma_1^{UP} |R_{mt}^{UP}| + \gamma_2^{UP} (R_{mt}^{UP})^2 + \epsilon_t \qquad (6)$$

where *CSAD* is the average cross-sectional absolute deviation of stock returns from the overall market return, $|R_{mt}^{DOWN}|$ is the absolute value of the average realized return of all available stocks during down market days, at time *t* and $|R_{mt}^{UP}|$ is the absolute value of the average realized return of all available stocks during up market days, at time *t*. $(R_{mt}^{DOWN})^2$ and $(R_{mt}^{UP})^2$ is the squares of the identical returns in down and up markets. By using the equation, significant and non-linear relation is expected between dispersion of stock returns and market return to detect herd behavior.

Absolute values of average market return in up and down markets, $|R_{mt}^{UP}|$ and $|R_{mt}^{DOWN}|$, are concerned with the size of the return, not with the sign of γ_1 coefficient to reveal the herd behavior. It provides a comparison between γ_1^{UP} and γ_1^{DOWN}. Significantly positive γ_1 coefficient indicates that CSAD increases with $|R_{mt}|$. Moreover, higher size in the up market than down market presents higher rate of increase, and vice versa. Thus, higher increase in the cross-sectional absolute valuation of the stocks indicates tendency of less herding. On the contrary, the negative sign and statistical significance of γ_2 coefficient is an indication of non-linear relation between CSAD and the average market return. It suggests that CSAD increases at a decreasing rate when the average market return increases hence providing strong evidence in favor of herding. Positive and statistically significant γ_2 coefficient indicates an evidence against the presence of non-linearity and herding implying that CSAD does not increase at a decreasing rate.

2.1.2. Empirical Studies Using Cross-Sectional Dispersions of Stock Returns Models

Many studies have attempted to investigate herd behavior by using the model developed by Christie and Huang (1995) and Chang, Cheng and Khorana (2000) in different international markets. Chen, Rui, and Xu (2003), Tan (2005), Demirer and Kutan (2006), Tan, Chiang, Mason and Nelling (2008), Chiang, Li and Tan (2010), and Liu (2012) have analyzed the existence of herding in Chinese Stock Markets.

Chen, Rui, and Xu (2003) have used the daily stock returns for the years 1996-2002 and have found no evidence on herding in either Shanghai or Shenzhen markets. With one exception that Shenzhen A shares and Shanghai B shares stand in contrast to the evidence of no herding in during extreme down markets.

Tan (2005) have examined the presence of herd behavior by using weekly data for both A and B shares listed on Shanghai and Shenzhen Stock Markets from 1995 to 2003 in his study. The regression results of weekly cross sectional absolute deviations indicated that herd behavior exists for both A markets. Additionally, while the stock returns don't deviate from the market return in up markets for Shanghai and Shenzhen

A shares, the positive and statistically significant coefficients indicate the absence of herd behavior in all four down markets.

Demirer and Kutan (2006) have also examined the existence of herd behavior by using daily stock returns of individual firms from 1999 to 2002 and daily sector indexes from 1993 to 2001 to analyze the herding. They have found no evidence of herding in either Shanghai or Shenzhen Stock Markets, supporting evidence to the findings of Chen, Rui, and Xu (2003) and Tan (2005).

Tan, Chiang, Mason and Nelling (2008) have extended earlier studies of the Chinese Stock Markets and investigated the existence of the herd behavior by analyzing not only daily and weekly but also monthly stock prices for both A and B shares in Shanghai Stock Market and Shenzhen Stock Market over the period from 1994 to 2003. Herd behavior has been observed in all four markets when using daily data in both down and up markets. However, the results of weekly return observations have indicated the presence of herd behavior in Shanghai A-share and Shenzhen B-share markets. Similar to the weekly results, herding has been observed only in the Shanghai B-share market for monthly observations. The weaker evidence of herd behavior displayed in weekly and monthly data is consistent with the observation that "herd behavior is a very short-lived phenomenon" (Christie and Huang, 1995: 35).

Chiang, Li and Tan (2010) have studied the herd behavior of investors in both Shanghai and Shenzhen Stock Markets. They have stated that while the herding has been observed in both A-share markets, it has not been observed in either B-share markets. Nevertheless, regression analysis have indicated that while the herd behavior exists in down markets for both A-share and B-share investors, it has been observed only for A-share investors in up markets.

Liu (2012) has used weekly stock data for A shares of Shanghai and Shenzhen Stock Markets for the years 2000-2009 to test the herd behavior. Liu has analyzed the dispersion of stock returns during both up and down market periods and found that investors do not herd in either down or up markets. As a deeper analysis, bubble and financial crisis periods between 2007 and 2008 have been investigated and no herding has been observed as well.

Lao and Singh (2011) have compared Chinese and Indian Stock Markets to examine the herd behavior on a daily and weekly basis by using cross sectional volatility of stock returns. The stock prices have been obtained from the Shanghai A-Share index, and the Bombay Stock Exchange index over the period 1999 to 2009. Although analysis of daily stock returns indicated strong evidence on herding in both the Chinese and the Indian Stock Markets, because of short-lived structure of herding, no evidence have been found when weekly data is used.

Gleason, Lee and Mathur (2003) have studied commodity futures traded on European exchanges, and Gleason, Mathur and Peterson (2004) have studied Exchange Traded Funds to measure the effects of herd behavior by using daily stock prices. Based on the methodology of cross sectional volatility of stock returns, the existence of herding has not been observed during periods of extreme market movements. Their results implied that the dispersion between stock prices and market return increases during periods of both down and up markets implying the absence of herding.

Al-Shboul (2012) and Henker, Henker & Mitsios (2006) have examined the herd behavior based on the methodology suggested by Christie and Huang (1995) and Chang, Cheng and Khorana (2000) in Australian Stock Market. Daily and monthly returns have been used and large dispersions of stock returns have implied no evidence of herding during large price movements in the study of Al-Shboul (2012). However, small dispersions in up and down markets indicating that Australian investors herd.

Henker, Henker & Mitsios (2006) have investigated market wide and sector herd behavior by using intraday and daily data. Except property trust sector, no impact of herd behavior has been observed on stock prices. The findings of property trust sector for both intraday and daily data indicate the existence of herd behavior in up and down markets.

The existence of herd behavior has also been tested on the Japanese Stock Market (Cajueiro and Tabak, 2009), on the Italian Stock Market (Caparrelli, D'Arcangelis and Cassuto, 2004), and on the Pakistani Stock Market (Javed, Zafar and Hafeez, 2013) by utilizing the method of cross-sectional volatility of daily stock returns. Cajueiro and Tabak (2009) have analyzed dispersions of stock prices on a daily basis. The findings are consistent with the existence of herd behavior in down markets. By contrast with the down markets, returns tend to diverge from the overall market return in up markets implying the absence of herding.

Caparrelli, D'Arcangelis and Cassuto (2004) have performed an analysis of daily stock returns from 1988 to 2001 in the Italian Stock Market. The regression results have indicated that dispersion of stock returns is higher and the probability of herding has been denied during the large price movements. Exceptionally, when they have analyzed the herd behavior during both extreme up and down market days, smaller stock return dispersions have been observed leading to a strong evidence on herding.

Javed, Zafar and Hafeez (2013) have investigated the existence of herd behavior by using monthly returns in Pakistan. No evidence of herding has been found during up and down market days consistent with the short-lived structure of herding.

Some of the researchers have carried out comparable studies on herding within different international markets. Economou, Kostakis and Philippas (2010) and Mobarek and Mollah (2013) have compared herd behaviors in four Mediterranean Stock Markets. Daily data obtained from Portugal, Italy, Greece and Spain (PIGS) has been analyzed by using the methodology of cross sectional volatility of stock returns. The findings of the study by Economou, Kostakis and Philippas (2010) indicate the presence of herd behavior only for Italian and Greek Stock Markets. There is an exception that during the global financial crisis, the dispersion has been observed in Portuguese Stock Market, as well, implying the existence of herd behavior. The results of the study by Mobarek and Mollah (2013) supported the existence of herd behavior during extreme market conditions, especially, during the global financial crisis and the Eurozone crisis.

Chiang and Zheng (2010) have utilized daily stock returns from 1988 to 2009 to investigate the herd behavior in developed, Asian and Latin American markets. Their sample covers the developed stock markets: Australia, France, Germany, Hong Kong, Japan, United Kingdom, and United States; Asian Markets: China, Indonesia, Malaysia, Singapore, South Korea, Thailand, and Taiwan; Latin American Markets: Argentina, Brazil, Chile, and Mexico. They have used the methodology of cross sectional volatility of stock returns proposed by Christie and Huang (1995) and Chang et. al. (2000). They have found herding effects on developed stock markets except the US and the Asian Markets in both up and down market days. The effects of herding have increased during the crisis periods. Exceptionally, in the United States and the

Latin American Markets, herd behavior has been observed only during the crisis periods.

As similar with the study of Chiang and Zheng (2010), Zheng (2010) has investigated the effect of crisis on herd behavior during the periods of 1988-2009. The sample consists of advanced markets: Australia, France, Germany, United Kingdom, and United States; Latin American markets: Argentina, Brazil, Chile, and Mexico; Asian markets: China, Hong Kong, Japan, South Korea, Taiwan, Indonesia, Malaysia, Singapore, and Thailand. By using the cross-sectional standard deviations of stock returns, the findings of the study indicated that herding exists in each stock market except the US and the Latin American Markets for both up and down periods. The effect of herding increases during the crisis periods, consistent with the results of Chiang and Zheng (2010),

The study by Chiang, Li, Tan and Nelling (2011) have investigated the herd behavior in ten Pacific-Basin markets involving Australia, Hong Kong, Japan, Singapore, United States, China, Indonesia, Malaysia, South Korea, Thailand, and Taiwan. By using the data from 1997 to 2009, they have provided evidence on herding in both up and down markets based on the methodology of cross sectional absolute deviations of stock returns.

Altay (2008), Coban (2009), Kapusuzoglu (2011), Dogukanlı and Ergun (2011) and Kayalıdere (2012) have used different data sets obtained from Borsa Istanbul to test herd behavior. Altay (2008) has used sector classification to examine herd behavior during the periods of 1997 and 2008 in Borsa Istanbul. Daily data of services, financial, industrial and investment trusts sectors have been analyzed by utilizing the method of cross-sectional standard deviations of stock returns. To test the existence of herding, Altay (2008) has also implemented another methodology based on the cross sectional volatility of beta coefficients of the stocks suggested by Hwang and Salmon (2001, 2004). Herd behavior has been found towards the market portfolio. However, by contrast with the results of Christie and Huang (1995), the effect of herding decreases during the crisis periods.

Coban (2009) has obtained daily stock returns from Borsa Istanbul between 1997 and 2007 and used the cross sectional standard deviations of stock returns to test herd behavior. Regression results indicated that dispersion between stock returns and market return increases rather than decreases hence providing evidence of no herding in Borsa Istanbul.

Kapusuzoglu (2011) has investigated the existence of herd behavior by using daily stock returns obtained from BIST 100 Index. In contrast with the study of Coban (2009), the results of the study have supported the presence of herding over the periods from 2000 to 2010.

Dogukanlı and Ergun (2011) have analyzed monthly returns different from the previous studies in Turkey to examine the presence of herding. The data set, obtained from BIST All Shares, covers the periods of 2000-2010. Consistent with the Lao and Singh (2011) and Javed, Zafar and Hafeez (2013), the monthly returns diverge from the average market return hence providing no evidence of herding.

Kayalidere (2012) has used daily logarithmic stock returns between 1997 and 2012 in Borsa Istanbul and has divided the analysis period into two sub-periods, 1997-2004 and 2005-2012 to test the presence of herding. The findings indicated that there is herding during extreme up price movements, and there is no evidence of herding during extreme down price movements. At the second sub-period, between 2005 and 2012, the effect of herding has decreased and smaller effect has been observed.

2.2. CROSS-SECTIONAL VOLATILITY OF BETA COEFFICIENTS

To detect herd behavior, a more comprehensive model which based on the cross-sectional dispersion of the beta coefficients was developed by Hwang and Salmon (2004). They have measured herd behavior relying on deviations of the asset betas from the equilibrium values expressed in Capital Asset Pricing Model (CAPM). When investors imitate the market trend, the CAPM betas will deviate from their equilibrium values. These deviations from the equilibrium risk and return relationship in a market and asset returns are affected by psychological biases such as investor sentiment. As a result, the cross-sectional dispersion of the betas of the stocks would be expected to be smaller and investors herd around the market (Amirat and Bouri, 2009: 1414).

This type of herding differs from the CSSD model which is developed by Christie and Huang (1995) and Chang et al. (2000) in several respects. First of all, whereas the CSSD method captures herding only during extreme market movements days, whereas beta herding can be observed in both extreme and normal market conditions. Moreover, investors tend to herd more, when they are likely to be relatively more confident about the future. On the contrary, when a crisis occurs, investors tend to herd less, because they turn to their fundamentals rather than overall market movements (Hwang and Salmon, 2004: 587). Additionally, beta is the best parameter to explain the stock returns on the market (Carvalho and Barajas; 2013: 117). Therefore, this methodology may capture herding better. It is also possible to find more accurate results by using this methodology rather than the methodology based on the cross-sectional absolute valuation which uses squares of market return as a herding indicator.

In addition, even if the results of CSSD measurement suggests evidence of herding, they do not necessarily show whether asset prices themselves are biased due to herding. Because, when investors have the same available information, they adopt similar behavior. While this type of behavior conflicts with the intentional herding, it indicates consistency with the spurious herding. Hwang and Salmon (2004) have also analyzed whether herd behavior is intentional or not by taking into account several factors that explain stock returns. If herding is still observed, when the factors are included in the model, it can be mentioned from the intentional herding rather than spurious herding (Hwang and Salmon, 2004: 587; Caparelli et al. 2004: 224; Pop, 2012: 5-6; Seetharem and Brittan, 2013: 94).

2.2.1. Methodology

In Christie and Huang (1995), the cross-sectional standard deviations of the stock returns was calculated and the regression analysis was employed by using two dummy variables. Hwang and Salmon (2001, 2004) have analyzed the cross-sectional dispersion of the beta coefficients rather than stock returns. Firstly, they have calculated beta coefficients of each stock return by using the CAPM formula.

$$E_t(r_{it}) = \beta_{imt} E_t(r_{mt}) \qquad (7)$$

where r_{it} is the excess return on asset *i* at time *t*, r_{mt} is the excess return on the market at time *t*, β_{imt} is the systematic risk measure, and E_t is conditional expectation at time *t*.

Based on the CAPM assumptions, β_{imt} is constant and does not change over time. However, Hwang and Salmon (2004: 589) have argued that the equilibrium CAPM relationship does not remain constant, equilibrium betas may change over time and may be biased when there is herding towards the market portfolio. They have assumed the following relationship between the equilibrium beta (β_{imt}) and its biased equivalent (β^b_{imt}) in the presence of herding towards the market;

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}\,(\beta_{mt} - 1) \qquad (8)$$

where $E_t^b(r_{it})$ and β_{imt}^b are the market's behaviorally biased conditional expectation on the excess returns of asset *i* and its beta at the time *t*, respectively, h_{mt} is a latent herding parameter that changes over time. When h_{mt} = 0, β_{imt} does not change, the equilibrium CAPM holds, and there is no herd behavior. When h_{mt} = 1, β_{imt} = 1, there is perfect herding and the expected excess return on asset *i* will be the same as that on the market portfolio, all assets will move in the same direction with the market portfolio. When 0 < h_{mt} < 1, beta herding exists in the market and the degree of herding depends on the magnitude of h_{mt} .

As discussed above, herding can be measured by h_{mt} , but h_{mt} is not observed easily, if the beta, β_{imt}, is not constant. To measure h_{mt} , Hwang and Salmon (2004: 592) have calculated the cross-sectional standard deviations of the betas by the following equation.

$$Std_c\,(\beta_{imt}^b) = Std_c\,(\beta_{imt})\,(1 - h_{mt}) \qquad (9)$$

where Std_c is the cross-sectional standard deviaiton.

To extract h_{mt} from Std_c (β_{imt}^b), a standard state space model are employed. At first, the logarithms of the Std_c (β_{imt}^b) equation on both sides are taken and it is obtained:

$$log\ [Std_c\,(\beta_{imt}^b)] = log\ [Std_c\,(\beta_{imt})] + log\ (1 - h_{mt})$$

Using the assumptions on Std_c (β_{imt}), it can be written:

$$log\ [Std_c\,(\beta_{imt})] = \mu_m + v_{mt} \qquad (10)$$

where μ_m = E [log [Std_c (β_{imt}]] and $v_{mt} \sim iid\ (0, \sigma_{m\vartheta}^2)$, and then

$$\log\,[Std_c\,(\beta^b_{imt})] = \mu_m + H_{mt} + v_{mt}$$

where H_{mt} = log (1 - h_{mt}).

H_{mt} is assumed to evolve over time and follow a mean zero Autoregressive(1) process:

$$log\,[Std_c\,(\beta^b_{imt})] = \mu_m + H_{mt} + v_{mt} \qquad (11)$$

$$H_{mt} = \emptyset_m\, H_{mt-1} + \eta_{mt}$$

where $\eta_{mt} \sim iid\,(0,\, \sigma^2_{m\eta})$.

log $[Std_c\,(\beta^b_{imt})]$ equation is the measurement equation and H_{mt} equation is the transition equation of the standard state space model. To extract latter, Hwang and Salmon (2004) have used the Kalman filter (see Appendix 1). A significant value of $\sigma^2_{m\eta}$ indicates the exisence of herd behavior, and a significant $\emptyset$ supports the *AR(1)* process with required stationary H_{mt} and $|\emptyset_m| \leq 1$.

As explained above, a volatile $Std_c\,(\beta^b_{imt})$ is expected in the presence of herding. To test the robustness of herd behavior, some variables reflecting the state of the market and macroeconomic fundamentals were included in the model. If H_{mt} is not significant when the effect of these variables are taken into account, changes in the $Std_c\,(\beta^b_{imt})$ could be explained by changes in these fundamentals rather than herding.

At first, the market volatility and the market return reflecting the state of the market were included as independent variables in the following estimation equation:

$$log\,[Std_c\,(\beta^b_{imt})] = \mu_m + H_{mt} + c_{m1}\, log\,\sigma_{mt} + c_{m2}\, r_{mt} + v_{mt} \qquad (12)$$

$$\mathrm{H_{mt}} = \emptyset_\mathrm{m}\, \mathrm{H_{mt-1}} + \eta_\mathrm{mt}$$

where log σ_{mt} is market log-volatility and r_{mt} is market return at time *t*.

Secondly, the size (small minus big, SMB) and book-to-market (high minus low, HML) factors of Fama and French (1993) were included as independent variables and the following model is then written:

$$log\,[Std_c\,(\beta^b_{imt})] = \mu_m + H_{mt} + c_{m1}\, log\,\sigma_{mt} + c_{m2}\, r_{mt} + c_{m3}SMB_t + c_{m4}HML_t + v_{mt} \qquad (13)$$

$$H_{mt} = \emptyset_m\, H_{mt-1} + \eta_{mt}$$

To test robustness of herding, Hwang and Salmon (2004) have formed one more alternative model, by adding macroeconomic variables such as the dividend price ratio (DP_t), the relative treasury bill rate (RTB_t), the term spread (TS_t), and the default spread (DSt).

$$log\ [Std_c\ (\beta^b_{imt})] = \mu_m + H_{mt} + c_{m1}\ log\ \sigma_{mt} + c_{m2}\ r_{mt} + c_{m5}DP_t + c_{m6}RTB_t + c_{m7}TS_t + c_{m8}DS_t + v_{mt} \qquad (14)$$

$$H_{mt} = \emptyset_m\ H_{mt-1} + \eta_{mt}$$

Herd behavior towards any other factor can also be measured by using standard linear factor model.

$$r_{it} = \alpha^b_{it} + \sum_{k=1}^{K} \beta^b_{ikt}\, f_{kt} + \varepsilon_{it},\ i = 1, \ldots, N \text{ and } t = 1, \ldots, T, \qquad (15)$$

where r_{it} is the excess return on asset *i* at time *t*, α^b_{it} is an intercept that changes over time, β^b_{ikt} are the coefficients on factor *k* at time *t*, f_{kt} is the realised value of factor *k* at time *t*, and ε_{it} is mean zero with variance σ^2_ε. As in conventional linear factor models, the excess market return is one of the factors (Hwang and Salmon, 2004: 17). Herding towards factor *k* at time *t*, h_{kt}, can then be formulated by

$$\beta^b_{ikt} = \beta_{ikt} - h_{kt}(\beta_{ikt} - E_c\,[\beta_{ikt}]) \qquad (16)$$

where $E_c\,[\beta_{ikt}]$ is cross-sectional expected beta for factor *k* at time *t*. To measure h_{kt}, Hwang and Salmon (2004) have calculated the cross-sectional standard deviations of β^b_{ikt} as,

$$Std_c\ (\beta^b_{ikt}) = Std_c\ (\beta_{ikt})\ (1 - h_{kt}) \qquad (17)$$

To extract h_{kt} from $Std_c\ (\beta^b_{ikt})$, the same estimation and transition models are developed with the equation of log [$Std_c\ (\beta^b_{imt})$],

$$\log\ [Std_c\ (\beta^b_{ikt})] = \mu_k + H_{kt} + v_{kt} \qquad (18)$$

$$H_{kt} = \emptyset_k\ H_{kt-1} + \eta_{kt}$$

where μ_k = E[log [$Std_c\ (\beta_{ikt})$]], $v_{kt} \sim iid\ (0, \sigma^2_{kv})$, $\eta_{kt} \sim iid\ (0, \sigma^2_{k\eta})$, and $H_{kt} = \log(1 - h_{kt})$.

As seen, the model enables to separate the effect of fundamental factors from herding. Hwang and Salmon (2004) have studied herding in the US and South Korean stock markets by using daily returns from 1 January 1993 to 30 November 2002. By contrast with the study of Christie and Huang (1995), it is observed that cross-sectional volatility of stock prices are independent from the fundamental values of the market, indicating the existence of herd behavior. They have also found evidence of herding for both rising and falling markets. Furthermore, the results indicate that developed markets such as the US show less herd behavior than developing markets such as the South Korea.

2.2.2. Empirical Studies Using Cross-Sectional Volatility of Beta Coefficients Model

The model based on the cross sectional volatility of stock returns is utilized for different periods within different stock markets to capture herd behavior. Wang (2008) has investigated herd behavior in 21 countries comparing the developed countries, the developing Latin American Markets and the developing Asian Markets. He has analyzed the size and book-to-market factors of the Fama-French three-factor model by monthly stock returns based on the methodology of cross-sectional volatility of stock returns from the period of 1985 to 2005. Consistent with the study of Hwang and Salmon (2001), it is observed that herding level in the developing Latin American and the developing Asian Markets is higher than the developed Markets.

Hassairi and Viviani (2011) has investigated herding by using Fama-French factors in European countries French, German, Italian and English stock markets are investigated as European markets with regard to herding. The method suggested by Hwang and Salmon (2004) is used. Herding is found in all countries, excluding periods of market turmoil and crisis. It is consistent with the assumptions of Hwang and Salmon (2004) which investors tend to herd more under normal market conditions rather than risky market conditions.

Pop (2012) has conducted his study in Romania to test the existence of herd behavior. He has measured beta herding by using the weekly excess returns covering the period from 2003 to 2012. Market volatility and macroeconomic factors have been used. He has concluded that herding level decreases during the market stress days such as crisis periods.

Messis, Zapranis and Kollias (2014) have analyzed the existence of herd behavior towards the market portfolio based on the CAPM approach. As similar with the study of Pop (2012), they have used macroeconomic variables such as gross domestic product (GDP), inflation, industrial production and 10Y Bond rate to detect herding. After they have found herding among investors, to test the contagion of herding, they have conducted the analysis to Germany, France, UK, US and China. The data covers the monthly returns from January 2000 to August 2011. As a result, herd behavior and contagion among countries are supported.

Gavriilidis, Kallinterakis, and Micciullo (2007) have studied the presence of herd behavior both during and after the Argentine financial crisis. They have obtained daily closing prices from Argentina’s main market index (MERVAL) between 2000 and 2006 and analyzed herd behavior based on the cross sectional volatility of beta coefficients which is developed by Hwang and Salmon (2004). Both during and after the financial crisis, their findings showed smaller cross-sectional dispersion of the stocks’ betas in Argentina stock market implying the existence of herd behavior.

Demirer, Kutan and Chen (2010) have investigated the presence of herd behavior in the Taiwanese stock market. Two different methodologies are compared to test herding over the January 1995 and December 2006 period by using a daily data set. While the first methodology suggested by Christie and Huang (1995) and Chang et al. (2000) indicates no evidence of herding, the methodology suggested by Hwang and Salmon (2004) indicates strong evidence of herding in the Taiwanese Market.

Seetharam and Britten (2013) have examined herd behavior between the periods of 1995 and 2011 in South Africa. Both the methodology of the cross-sectional dispersions of the stock returns and cross-sectional volatility of beta coefficients have been used to test the existence of herding. The results of these two methodologies indicate that while investors mimick the others during the periods of down market movement days, they do not follow the market trend during up market movement days.

As mentioned earlier, Altay (2008) has used cross-sectional dispersions of stock returns to test herd behavior by using daily stock returns between the periods of 1997 and 2008 in Borsa Istanbul within services, financial, industrial and investment trusts sectors. He has found herding among investors for the whole market. To compare the results, he has implemented another methodology based on the cross sectional volatility of beta coefficients of the stocks. Accordingly, investors tend to herd for the whole market except the periods of December 2003-April 2004 and May-October 2006 during extreme up and down price movements.

2.3. LAKONISHOK, SHLEIFER AND VISHNY (LSV) MEASURE

LSV measure developed by Lakonishok, Shleifer and Vishny (1992) is used to detect herd behavior based on the number of shares held rather than stock returns. This method aims to evaluate not only herding but also positive feedback trading among pension fund managers. Herding which is the first dimension of the analysis is defined in their study as buying (selling) the same stocks as others buy (sell). The second dimension, positive feedback trading, relies on the past performances of the stocks. Managers buy the stocks which are past winners and sell the stocks which are past losers.

Bikhchandani and Sharma (2000: 14) explain LSV herding measurement as “the average tendency of a group of money managers to buy (sell) particular stocks at the same time, relative to what could be expected if money managers traded independently”. The other explanation for herding is “the excess proportion of money managers buying (selling) a given stock in a given quarter. This excess is computed referring to the normal proportion of buyers (sellers) of all market stocks between fund managers (Bellando, 2010: 2-3).

As seen, this methodology measures the herding activity with regard to number of buyers and sellers to compute the proportion of stock holdings. Lakonishok et al. (1992: 29) explain this type of herding measurement with an example. They assume when 50% of the pension fund managers increases their holdings, the rest 50% of the managers decreases, indicating no evidence of herding. However, if 70% of the fund managers increases their holdings, 30% of them decreases. This result is an indicator of herd behavior between the managers. Because most of the managers have decided to invest on the same side of the market.

2.3.1. Methodology

LSV measure of herding for a given stock *i* at time *t* is analyzed by the following formula.

$$H(i) = |B(i)/(B(i) + S(i)) - p(t)| - AF(i) \qquad (19)$$

where *B(i)* is the number of money managers who buy the stock *i*, *S(i)* is the number of money managers who sell the stock *i*, *p(t)* is the proportion of buyers, and *AF(i)* is the adjustment factor.

H(i) is expected to be a positive value for the existence of herding. *H(i),* which is equal to zero, is an indicator of no herding.

Lakonishok et al. (1992) have investigated the effect of trading on stock prices by using the holdings of 769 pension funds from the first quarter of 1985 to the last quarter of 1989 in US market. The results indicate that while there is no significant herding among pension fund managers, they tend to herd more in small stocks in comparison with large stocks based on stocks' past prices.

2.3.2. Empirical Studies Using Lakonishok, Shleifer and Vishny (LSV) Measure

Most of the empirical studies have used LSV measure to test herd behavior among managers and investors in different stock markets. Wylie (2005) has investigated the accuracy of LSV herding measure by using the portfolio holdings of 268 equity mutual funds in UK. The results indicate the existence of herding among the UK mutual fund managers, especially for the smallest and the largest stocks. Moreover, he has argued that the methodology suggested by Lakonishok et. al. (1992) is suitable to measure herd behavior.

Merli and Roger (2013) have employed nearly 8 million trades by 87,373 French individual investors between 1999 and 2006 to test the existence of herd behavior. It is found that individuals show the persistence of herding over time. Furthermore, the relation between the past performance and herd behavior exists. Investors gather information of the past performance of others to decide whether they herd or not. If they had negative performance in the past, they prefer to decide based on his own information and predict herding for the next period. It can be also concluded that sophisticated investors are less inclined to herd behavior. Investors who take more risk, do not follow the others and have extreme returns.

Wermers (1999) has tested the presence of trading activity of the mutual fund managers. LSV measure has been utilized to evaluate the behaviors of fund managers between the periods of 1975 and 1994 in United States. The impact of herding on stock prices is observed among small stocks, consistent with the results of Lakonishok, et al. (1992). Wermers (1999) has also emphasized the effect of positive feedback trading strategy that managers buy the stock if its past return is high, and sell if its past return is low.

Choe, Kho and Stulz (1999) measure herd behavior among foreign investors in Korea. The data covers the period from November 30, 1996 to the end of 1997. They have found that foreign investors follow the crowd before Korea's crisis, but crisis period is the turning point and herding level decreases during this period. This result is consistent with the assumptions of Hwang and Salmon (2004) who argue that investors turn to their fundamentals rather than herding during the crisis periods, because of the uncertain information.

Grinblatt, Titman and Wermers (1995) have investigated whether US mutual fund managers exhibit herd behavior and positive feedback trading. Quarterly portfolio holdings for 274 mutual funds have been used for testing. As a result, while a weaker evidence of herding is observed, mutual fund managers tend to buy past winner stocks and sell past loser ones, as found by Wermers (1999).

Nofsinger and Sias (1999) have evaluated the impact of herding and positive feedback trading activity on stock returns in US stock market. Monthly stock returns, annual market capitalization and annual proportion of shareholdings of investors have been used from 1977 to 1996. It can be concluded that the evidence of herding is supported at much higher levels for institutional investors than individuals. Institutional investors also indicate stronger positive feedback trading on stock returns. The only study, applied in Borsa Istanbul, is a dissertation which is written by Gökdemir (2010). He has studied the presence of herding and positive feedback trading among foreign investors by using LSV measure developed by Lakonishok et al. (1992). Net purchases and net sales including 297 stocks, obtained from Borsa Istanbul, have been utilized for the period from January 1997 through December 2006. His findings suggest that foreign investors, trading on Borsa Istanbul, although not always, imitate the others, indicating weaker evidence of herding. Moreover, the findings of the study imply that foreign investors decide based on the past performance of the stocks, indicating tendency with positive feedback strategy.

CHAPTER THREE
DATA AND METHODOLOGY

In this chapter, firstly, the aims and the hypotheses of the study are presented. Then, the two measurement methods that are used to test herd behavior and the relevant data are explained. At last, the descriptive statistics are reported.

3.1. THE AIMS AND HYPOTHESES

The main purpose of this study is to measure the existence of herd behavior in Borsa Istanbul from three perspectives: cross-sectional standard deviation of stock returns; cross-sectional absolute valuation of stock returns; cross-sectional volatility of beta coefficients.

The cross-sectional standard deviation of stock returns (CSSD) measures the volatility of returns around the market index. The purpose of this measurement is twofold:

- To find out whether there is herd behavior or not in up and down market movement days.
- To discuss herd behavior within session one and session two markets.

Two hypotheses are tested within stock dispersions in this study.

Hypothesis 1:
H_0: There is no herd behavior during up market movement days in Borsa Istanbul.
H_1: There is herd behavior during up market movement days in Borsa Istanbul.

Hypothesis 2:
H_0: There is no herd behavior during down market movement days in Borsa Istanbul.
H_1: There is herd behavior during down market movement days in Borsa Istanbul.

These two hypotheses will be tested for different samples in this study. At first, daily returns will be tested for the whole period, and then intraday returns will be tested to detect herding in session one and session two markets. This analysis aims to compare daily and intraday returns in terms of herding activity. This also provides opportunity to examine whether herd behavior is a very short-lived phenomenon or not in Borsa Istanbul.

The second measurement based on the cross-sectional absolute valuation of stock returns (CSAD) aims to investigate the presence of herd behavior in Borsa Istanbul. A non-linear relation between market return and stock dispersion is expected in the presence of herding. In this study, three hypotheses are developed within the cross-sectional absolute valuation of the stocks. Additionally, the presence of this linear relationship is also analyzed in terms of session one and session two markets; as well as up and down markets.

Hypothesis 3:

H_0: There is no herd behavior if the relation between market return and stock dispersion is linear in Borsa Istanbul.

H_1: There is herd behavior if the relation between market return and stock dispersion is not linear in Borsa Istanbul.

Hypothesis 4:

H_0: There is no herd behavior if the relation between market return and stock dispersion is linear during up market movement days in Borsa Istanbul.

H_1: There is herd behavior if the relation between market return and stock dispersion is not linear during up market movement days in Borsa Istanbul.

Hypothesis 5:

H_0: There is no herd behavior if the relation between market return and stock dispersion is linear during down market movement days in Borsa Istanbul.

H_1: There is herd behavior if the relation between market return and stock dispersion is not linear during down market movement days in Borsa Istanbul.

The cross-sectional volatility of beta coefficients measures the volatility of asset betas from the equilibrium values expressed in capital asset pricing model (CAPM). The purpose of this measurement is twofold:

- To analyze herding during not only up and down market movement days but also normal market movement days.
- To capture herding by taking into account several factors such as market volatility, market return, size and book-to-market ratio.

One main hypothesis is tested within cross-sectional volatility of beta coefficients in this study. It will also be tested for the whole period, session one and session two markets.

Hypothesis 6:
H_0: There is no herd behavior in Borsa Istanbul.
H_1: There is herd behavior in Borsa Istanbul.

The cross-sectional volatility of beta coefficients also provides opportunity to evaluate changes in herding level and to differentiate intentional and spurious herding. If the existence of herding does change when market volatility, market return, size and value factors are included then it can be said that herding is spurious and changes in cross-sectional volatility can be explained by changes in these fundamentals rather than herding. Thus, investors do not herd after observing others, instead follow the market trend as a reaction to public information (Hwang and Salmon, 2004: 587).

In this context, if herd behavior is observed in Borsa Istanbul, one sub-hypothesis is tested in this study.

Hypothesis 7:
H_0: There is no intentional herd behavior in Borsa Istanbul.
H_1: There is an intentional herd behavior in Borsa Istanbul.

This study is the first comprehensive attempt to measure herding in terms of market volatility, market return, size and book-to-market ratio factors in Borsa Istanbul. This study also contributes to the international literature in the field of behavioral finance by measuring similar variables that were used in the earlier studies and strengthening their theoretical and empirical frameworks[2]. Furthermore, this is the first study that covers such an extensive period (1988-2014) and compares daily and intraday stock returns to evaluate herd behavior in Borsa Istanbul.

3.2. DATA AND METHODOLOGY

As mentioned earlier, cross-sectional dispersion of stock returns suggested by Christie and Huang (1995) and developed by Chang et al. (2000) and cross-sectional volatility of beta coefficients suggested by Hwang and Salmon (2004) are used to test the presence of herd behavior among investors in Borsa Istanbul.

3.2.1. Methodology of Cross-Sectional Dispersion of Stock Returns

The methodology based on the cross-sectional dispersion of stock returns measures the volatility of stock returns around overall market return. Dispersions between stock returns and market return are expected to be small during up and down market movement days in the presence of herding (Christie and Huang, 1995; Chang et al., 2000).

3.2.1.1. Data for Cross-Sectional Dispersion of Stock Returns

The research population is composed of stocks traded on Borsa Istanbul. Their daily closing prices were obtained between the periods from 14th January 1988 to 31st December 2014. Daily closing prices of BIST 100 index were selected as the market indicator. The data also enables to analyze and compare intraday closing prices starting from 2nd January 1995. The stock prices are reported in Borsa Istanbul as two sessions, session one and session two. While the trading hours of session one is from 09.15 am to 12.30 pm, the trading hours of session two is from 02.00 pm to 05.40 pm. There are 6417 daily observations and 9559 intraday observations in Borsa Istanbul for the study

[2] In international literature, earlier studies analyzed herding based on size and book-to-market ratio (Wang, 2008; Hassairi and Viviani, 2011), market volatility and market return (Pop, 2012). In Turkey, Altay (2008) investigated herding by using the CAPM approach excluding market volatility, market return, size and book-to-market ratio.

period. There were 47 stocks at the beginning of 1988 and 441 stocks at the end of 2014.

Daily closing prices of BIST 100 Index were obtained from the official website of the Borsa Istanbul from 1988 to 2014. However, daily closing prices of the stocks could not be obtained from the official website from 1988 to 1998; therefore daily transaction data were requested between the periods of 1988 and 1998 from Borsa Istanbul. Daily data after 1998 for the stocks were collected from the official website of Borsa Istanbul. Daily and intraday closing prices were converted to daily and intraday logarithmic returns to calculate the dispersions. The following formula (20) was used to calculate returns:

$$R_{i,t} = ln\ (P_{i,t} / P_{i,t-1}) \qquad (20)$$

where $R_{i,t}$ is the return of stock i at time t, $P_{i,t}$ is the closing price of stock i at time t, and $P_{i,t-1}$ is the closing price of stock i on the day before.

3.2.1.2. Models of Cross-Sectional Dispersion of Stock Returns

To detect herd behavior, stock dispersions around the market return are analyzed during up and down market movement days. To calculate stock dispersions, two different methodologies are used: cross-sectional standard deviation of the stocks and cross-sectional absolute valuation of the stocks.

3.2.1.2.1. Model of Cross-Sectional Standard Deviation of Stock Returns

Cross-sectional standard deviation is calculated by using the stock returns which are calculated using closing prices, to measure dispersion of the stocks, as explained in the previous chapter:

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

where CSSD is the cross-sectional standard deviation of stock returns, N is the number of firms in the portfolio, $R_{i,t}$ is the observed stock return of firm i at time t, $R_{m,t}$ is the cross-sectional average of N returns in the portfolio at time t.

To examine up and down market movement days, two dummy variables are taken into account and used in the following regression equation.

$$CSSD_t = a + \beta^D D^D{}_t + \beta^U D^U{}_t + \epsilon_t$$

where $D^D{}_t$ is equal to one if the BIST 100 index return on day t lies below the 1 % and 5 % of the return distribution and equal to zero otherwise, $D^U{}_t$ is equal to one if the BIST 100 index return on day t lies above the 1 % and 5 % of the return distribution and equal to zero otherwise.

Negative and statistically significant coefficient of β^D and β^U are indicators of small dispersions between stock returns and BIST 100 index return. It can be said that in this case stock returns do not diverge from the overall market return. Thus, H_0 will be rejected and it can be concluded that there is herd behavior during up (*Hypothesis 1*) and down (*Hypothesis 2*) market movement days in Borsa Istanbul. Moreover, Christie and Huang (1995) state that even if herding is not found for up and down markets, lower coefficient indicates that stock returns diverge from the market index less and hence investors tend to herd.

The same CSSD model is also conducted to measure the existence of herd behavior during up and down market movements in session one and session two markets rather than overall market. If coefficients of β^D and β^U are negative and statistically significant, H_0 will be rejected again, indicating herd behavior for both up and down market movement days in session one and session two markets.

3.2.1.2.2. Model of Cross-Sectional Absolute Valuation of Stock Returns

An extended methodology based on the cross-sectional absolute valuation of the stocks developed by Chang, Cheng and Khorana (2000) is also used to test herd behavior. This model measures whether the relation between stock dispersions and market return is linear or not. Non-linearity is expected in the presence of herding.

Firstly, cross-sectional absolute valuation is expressed as:

$$CSAD_t = \frac{\sum_{t=1}^{N} |R_{i,t} - R_{m,t}}{N}$$

where CSAD is the cross-sectional absolute deviation of stock returns, N is the numbers of firms in the portfolio, $R_{i,t}$ is the observed stock return of firm i at time t, $R_{m,t}$ is the cross-sectional average of N returns in the portfolio at time t, as mentioned in the previous chapter.

A quadratic equation is used to investigate the presence of herd behavior by using the following formula.

$$CSAD_t = a + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t})^2$$

where $R_{m,t}$ is the average market return of the sample, at time *t*.

The negative and statistically significant γ_2 coefficient indicates non-linearity hence resulting herd behavior. Thus, H_0 will not be supported and it can be concluded that there is herd behavior if there is non-linearity between market return and stock dispersion in Borsa Istanbul (*Hypothesis 3*).

Following Chang, Cheng and Khorana (2000), a comprehensive regression analysis is conducted to capture the linearity between stock dispersions and market return in up and down market movement days in Borsa Istanbul.

$$CSAD_t^{DOWN} = a + \gamma_1^{DOWN} |R_{mt}^{DOWN}| + \gamma_2^{DOWN} (R_{mt}^{DOWN})^2 + \epsilon_t$$

$$CSAD_t^{UP} = a + \gamma_1^{UP} |R_{mt}^{UP}| + \gamma_2^{UP} (R_{mt}^{UP})^2 + \epsilon_t$$

where CSAD is the average cross-sectional absolute deviation of stock returns from the overall market return, $|R_{mt}^{DOWN}|$ is the absolute value of the average realized return of all available stocks during down market days, at time *t* and $|R_{mt}^{UP}|$ is the absolute value of the average realized return of all available stocks during up market days, at time *t*. $(R_{mt}^{DOWN})^2$ and $(R_{mt}^{UP})^2$ is the squares of the identical returns in down and up markets. By using the equation, non-linear relation is expected between dispersion of stock returns and market return to detect herd behavior. The negative sign and statistically significant of γ_2 coefficient indicates a non-linear relation between CSAD and market return. It suggests that CSAD increases at a decreasing rate when the average market return increases hence providing evidence in favor of herding. Thus, H_0 will be rejected and it can be concluded that there is herd behavior if there is non-linearity between stock dispersions and market return in up and down market movement days (*Hypothesis 4 and Hypothesis 5*). Additionally, positive coefficient of γ_1 indicates that CSAD increases with the size of market. Thus, when CSAD increases more in up markets, investors tend to herd less, and vice versa.

To compare the results of daily and intraday data, the model is also conducted to session one and session two markets and tested the existence of non-linearity between market return and stock dispersion, indicating evidence of herding in session one and session two markets. In the presence of herding, H_0 will be rejected, again, for up (*Hypothesis 4*) and down (*Hypothesis 5*) market movement days in session one and session two markets.

3.2.1.3. Descriptive Statistics for Cross-Sectional Dispersion of Stock Returns

Descriptive statistics for cross-sectional dispersion of stock returns are presented on daily and intraday basis.

3.2.1.3.1. Descriptive Statistics for Daily Data

The descriptive statistics of cross-sectional standard deviation of the stocks (CSS*D*), cross-sectional absolute valuations of the stocks (CSAD) and BIST 100 Index returns calculated on daily observations are presented between 14.01.1988 and 31.12.2014 in Table 1. The number of observations for all variables is 6417.

The highest mean value is observed for cross-sectional standard deviation of the stocks is 0.1151, while the lowest one is found for the market return as 0.000698. The maximum CSSD is 0.952117 on 23.08.1995 and the minimum is 0.012788 on 22.06.2012. The maximum CSA*D* is 0.208612 on 04.01.1991 and the minimum is 0.008382 on 12.10.2012. The maximum index return is 0.102795 on 07.12.1990 and the minimum is -0.126130 on 17.12.1990.

CSSD's higher mean value accompanies with higher standard deviation value. The standard deviation of CSSD is higher than the standard deviation of CSAD indicating CSSD deviates from the average value more than CSAD. Higher standard deviation indicates unexpected market events and cross-sectional variations. Chiang and Zheng (2010: 1915) state that lower standard deviation indicates smaller dispersions from average market return, and increases the possibility of herding.

The Jargue-Bera test shows non-normal distribution. The p-values are statistically significant for CSSD, CSAD and market return variables at 1 % level. The

Table 1. Descriptive Statistics of Daily Data

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jargue-Bera	Probability	Observations
CSAD	0.032364	0.026879	0.208612	0.008382	0.018920	1.953.591	9.807.474	16472.38	0.000000	6417
CSSD	0.115100	0.049157	0.952117	0.012788	0.121204	1.619.829	6.039.728	5.276.734	0.000000	6417
Market Return	0.000698	0.000205	0.102795	-0.126130	0.020866	0.047617	6.873.724	4.014.584	0.000000	6417

skewness values of the CSSD and CSAD provides asymmetrical distribution. The distribution is positively skewed for both of them. Positively skewed means that the distribution is skewed right. However, the market return is also positively skewed but lower than both CSSD and CSAD. Its skewness is near zero and it provides closer distribution to the left and right of the center point. In addition, they do not have a distinct and sharper peak, because kurtosis values of these variables are not so high.

3.2.1.3.2. Descriptive Statistics for Intraday Data

Table 2 shows the descriptive statistics of cross-sectional standard deviations of the stocks (CSSD), cross-sectional absolute valuation of stocks (CSAD) and BIST 100 Index returns using intraday data between 02.01.1995 and 31.12.2014.

The number of observations for all variables is 4793 in session one market. The highest mean value is observed for cross-sectional standard deviation of the stocks is 0.1266, while the lowest one is found for market return as 0.0125, similar to the daily data. The maximum CSSD is 1.237870 and the minimum is 0.013357. The maximum CSAD is 0.283084 and the minimum is 0.009201. The maximum index return is 0.103093 and the minimum is -0.027411.

Higher mean value of CSSD can be explained with higher standard deviation value. As seen in Table 2, the standard deviation of CSSD is higher than the standard deviation of CSAD resulting that CSSD diverges from the average value more than CSAD. Higher standard deviation is also an indicator of the market’s high cross-sectional variations. As stated earlier, Chiang and Zheng (2010: 1915) argue that these variations could be because of the unexpected market events. Moreover, lower standard deviation is an indicator of smaller dispersions from average market return, consistent with the existence of herding.

The Jargue-Bera test shows non-normal distribution. The p-values are statistically significant for CSSD, CSAD and market return variables at 1 % level. The skewness values of the CSSD, CSAD and market return do not exhibit a symmetrical distribution. The distribution is positively skewed, thus skewed right, for all of them.

Table 2. Descriptive Statistics of Intraday Data

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jargue-Bera	Probability	Observations
					Descriptive Statistics for Session One Market					
CSAD	0.031622	0.026675	0.283084	0.009201	0.018999	2.926242	26.04639	60708.51	0.000000	4793
CSSD	0.126574	0.069323	1.237870	0.013357	0.124383	1.423356	6.193015	1964.868	0.000000	4793
Market Return	0.012457	0.008623	0.103093	-0.027411	0.012733	2.535750	12.60745	12672.73	0.000000	4793
					Descriptive Statistics for Session Two Market					
CSAD	0.031416	0.027271	0.142633	0.008382	0.016823	1.415667	5.919709	1629.992	0.000000	4766
CSSD	0.132922	0.079084	0.952117	0.013018	0.125799	1.190988	4.330800	733.6271	0.000000	4766
Market Return	0.011324	0.008295	0.092113	-0.055789	0.011222	2.127005	10.98532	8066.807	0.000000	4766

The most heavily peaked distribution is observed for CSAD because of its excess kurtosis value.

The descriptive statistics of session two market are also reported in Table 2. The data ranges from 02.01.1995 to 31.12.2014. There are 4766 observations for session two.

The highest mean value is presented for cross-sectional standard deviation of the stocks is 0.1329, while the lowest one is found for market return as 0.0113. The maximum CSSD is 0.952117 and the minimum is 0.013018. The maximum CSAD is 0.142633 and the minimum is 0.008382. The maximum index return is 0.092113 and the minimum is -0.055789.

Higher standard deviation value found for CSSD is consistent with the mean value of CSSD. The standard deviation of CSSD is higher than the standard deviation of CSAD, as observed in the session one market. It indicates that CSSD deviates from the average value more than CSAD. Higher standard deviation shows larger dispersions from the average market return and decreases the probability of herd behavior.

The Jargue-Bera values exhibit non-normal distribution. The p-values are statistically significant for CSSD, CSAD and market return variables at 1% level. The skewness values of the CSSD, CSAD and market return provides asymmetrical distribution. The distribution is positively skewed for all of them. Positively skewed can be shown with the rightly skewed distribution.

3.2.2. Methodology of Cross-Sectional Volatility of Beta Coefficients

Following Hwang and Salmon (2004), the methodology based on the cross-sectional volatility of beta coefficients was employed to investigate herd behavior in Borsa Istanbul. This method measures the variability of the betas rather than stock returns.

3.2.2.1. Data for Cross-Sectional Volatility of Beta Coefficients

Daily closing prices of the stocks and the market were also obtained. The sample includes daily data ranges from 2nd January 1990 to 31th December 2014. Intraday data were also analyzed starting from 2nd January 1995 and BIST 100 Index, which were obtained from the official website of the Borsa Istanbul, was selected as the market return. There are 6215 daily and 9724 intraday observations for Borsa Istanbul and the number of stocks has increased from 63 to 441 for the study period. As mentioned before, daily closing prices of the stocks could not be obtained from the official website from 1990 to 1998. Daily transaction data were requested between the periods of 1990 and 1998 from Borsa Istanbul. Daily data after 1998 for the stocks were collected from the official website of Borsa Istanbul.

To convert daily and intraday closing prices to logarithmic stock returns, equation of $R_{i,t}$, which is explained earlier, was used.

3.2.2.2. Models of Cross-Sectional Volatility of Beta Coefficients

To be used in the analysis of cross-sectional standard deviation, beta coefficients were calculated by the following formula:

$$E_t(r_{it}) = \beta_{imt} E_t(r_{mt})$$

where r_{it} is the excess return on asset i at time t, r_{mt} is the excess return on the market at time t, β_{imt} is the systematic risk measure, and E_t is conditional expectation at time t.

Daily returns and risk-free rate (r_f) were used to calculate the excess returns on asset i and the market at time t (r_t - r_f). As the risk-free rate, starting from the 1990s, yearly compounded interest rates of treasury discounted auctions were obtained from the official website of Undersecretariat of Treasury (www.treasury.gov.tr) and converted to daily rates[3].

To obtain the cross-sectional standard deviation of the beta coefficients on the market portfolio, the following equation was used as in Hwang and Salmon (2004):

[3] Daily interest rates are calculated by dividing yearly interest rates to number of months in one year, number of weeks in one month and then, number of days in one week, as in Altay (2008).

$$Std_c(\beta^b_{imt}) = \sqrt{\frac{\sum_{i=1}^{N_t}(\beta^b_{imt} - \overline{\beta^b_{imt}})^2}{N_t}}$$

where $\overline{\beta^b_{imt}} = \frac{1}{N_t}\sum_{i=1}^{N_t}\beta^b_{imt}$ and N_t is the number of stocks in month *t*. To examine herding level over time, firstly, logarithms of the equation were taken as $\log Std_c\ (\beta^b_{imt})$ and then the following regression equation is analyzed:

$$\log\ [Std_c\ (\beta^b_{imt})] = \mu_m + H_{mt} + v_{mt}$$

$$H_{mt} = \emptyset_m\ H_{mt-1} + \eta_{mt}$$

where $\eta_{mt} \sim iid\ (0,\ \sigma^2_{m\eta})$.

The equation of log $[Std_c\ (\beta^b_{imt})]$ is the measurement equation and the equation of H_{mt} is the transition equation of the standard state space model. To extract H_{mt}, the standard state space model was applied by using Kalman Filter (Appendix 1), as in Hwang and Salmon (2004). A significant H_{mt} is expected in the existence of herding. Thus, H_0 will be rejected and it can be concluded that there is herd behavior in Borsa Istanbul (*Hypothesis 6*). The magnitude of H_{mt} indicates the degree of herding. For instance, if H_{mt}=1, there is perfect herding.

To test the robustness of herd behavior in Borsa Istanbul, market volatility, market return, size and book-to-market factors were added to the model. If insignificant H_{mt} is found when these variables are included, changes in the Std_c (β^b_{imt}) can be explained by changes in these factors rather than herd behavior (Hwang and Salmon, 2004). Then, herding found in Borsa Istanbul is evaluated as spurious herding.

Cross-sectional volatility of the betas is also analyzed for session one and session two markets to compare daily and intraday results. H_0 will not be supported again in the presence of herding in session one and session two markets in Borsa Istanbul (*Hypothesis 6*).

3.2.2.2.1. Model Including Market Volatility and Market Return

Market volatility and market return were taken into consideration as independent variables as in Hwang and Salmon (2004) in the following estimation equation:

$$log\ [Std_c\ (\beta^b_{imt})] = \mu_m + H_{mt} + c_{m1}\ log\ \sigma_{mt} + c_{m2}\ r_{mt} + v_{mt}$$

$$H_{mt} = \emptyset_m\ H_{mt-1} + \eta_{mt}$$

where log σ_{mt} is market log-volatility and r_{mt} is market return at time *t*.

BIST 100 index daily returns are used as an indicator of market return between the periods of 1990 and 2014. To calculate market volatility values (σ_{mt}), squared daily returns were used as in Schwert (1989):

$$\sigma^2_{mt} = \sum_{i=1}^{N_t}(r_{it} - \overline{r_t})^2 \qquad (21)$$

where $\overline{r_t}$ is the sample mean of the daily market returns and r_{it} is the daily market returns in month *t*, respectively. N_t is the number of daily returns in month *t*.

Statistically significant H_{mt} is also expected in the existence of herd behavior and the magnitude of H_{mt} also indicates the degree of herding. If H_{mt} is still significant when the market volatility and market return added, then, H_0 will not be supported and it can be concluded that there is an intentional herding rather than spurious herding in Borsa Istanbul (*Hypothesis 7*). Thus, investors move in the same direction independent from the market volatility and market return. Moreover, negative and significant coefficients of log σ_{mt} and r_{mt} are indicators of non-linearity between the market variables and herd behavior.

3.2.2.2.2. Model Including Size and Book-to-Market Factors of Fama-French Model

Following Hwang and Salmon (2004), the size (small minus big, SMB) and book-to-market (high minus low, HML) factors of Fama and French (1993) were also added to the model as independent variables and the following model is then written:

$$log\ [Std_c\ (\beta^b_{imt})] = \mu_m + H_{mt} + c_{m1}\ log\ \sigma_{mt} + c_{m2}\ r_{mt} + c_{m3}SMB_t + c_{m4}HML_t + v_{mt}$$

$$H_{mt} = \emptyset_m\ H_{mt-1} + \eta_{mt}$$

where log σ_{mt} is market log-volatility and r_{mt} is market return, SMB_t is size (small-minus-big) factor and HML_t is book-to-market (high-minus-low) factor at time *t*.

To obtain size (small-minus-big) and book-to-market (high-minus-low) factors, 6 size-BE/ME (book-to-market) portfolios based on the stocks were formed, following Fama and French (1993).

Firstly, to calculate small-minus-big values, in June of each year t from 1995 to 2014, all stocks have been ranked based on their sizes which were requested from Borsa Istanbul. By using the median value of these size values, they were divided into two groups as small and big.

For high-minus-low values, book-to-market values were also obtained from the official website of Borsa Istanbul. In December of each year t-1 from 1995 to 2014, book-to-market values have been ranked and divided into three groups They are broken as bottom (30%), middle (40%) and top (30%) for the sample stocks. The stocks with the negative book values were not used as in Fama and French (1993).

It is expected that H_{mt} is significant in the presence of herding. If the significance of H_{mt} does not change when the size and book-to-market factors are included in the model, H_1 will be supported again it can be said that there is an intentional herding rather than spurious herding in Borsa Istanbul (*Hypothesis 7*). Thus, investors follow the market trend independent from the changes of size and book-to-market values. Moreover, negative and significant coefficients of SMB_t and HML_t are indicators of non-linearity between Fama-French factors and herd behavior.

3.2.2.3. Descriptive Statistics for Cross-Sectional Volatility of Beta Coefficients

Descriptive statistics for cross-sectional volatility of beta coefficients are presented on daily and intraday basis.

3.2.2.3.1. Descriptive Statistics for Daily Data

The descriptive statistics of the variables, which are used to be analyzed in Hwang and Salmon (2004) model, are presented on daily basis, covering the period from 02.01.1990 to 31.12.2014 in Table 3. The number of observations for all variables is 6215.

Table 3. Descriptive Statistics of Daily Data

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jargue-Bera	Probability	Observations
log [$Std_t(\beta^b_{imt})$]	-0.240344	-0.288859	3.212632	-1.500388	0.689052	0.480534	2.582985	267.7111	0.000000	6215
H_{mt}	-0.000765	-8.94E-05	0.007283	-0.222542	0.005091	-24.03042	814.4700	1.61E+08	0.000000	6215
log σ_{mt}	0.079719	0.067096	0.299843	0.000000	0.045720	1.670733	6.392974	5671.307	0.000000	6215
r_{mt}	0.000565	0.000221	0.102795	-0.126130	0.020274	0.029204	7.305094	4635.856	0.000000	6215
β^b_{imt}	1.001034	0.994880	36.99786	-280.4282	3.796736	-69.36898	5160.484	6.49E+09	0.000000	6215
$Std_t(\beta^b_{imt})$	2.606492	0.514210	1631.667	0.031595	24.95786	55.74278	3397.404	2.81E+09	0.000000	6215
SMB_t	0.001608	0.000239	0.276416	-0.221856	0.030294	0.194282	9.555362	8427.099	0.000000	6215
HML_t	0.000740	8.17E-07	0.441885	-0.334051	0.045784	0.403584	15.52824	30799.27	0.000000	6215

As shown in Table 3, the highest mean value is reported for cross-sectional standard deviation of the betas is 2.6065 while the lowest one is found for logarithms of cross-sectional standard deviation as -0.240344. The maximum value of standard deviation is 1631.667 and the minimum value is 0.031595. The maximum value of the logarithms of cross-sectional standard deviation is 3.212632 and the minimum value is -1.500388. The maximum value of the logarithms of cross-sectional standard deviation is 3.212632 and the minimum value is -1.500388.

It is also seen from the table that the skewness value of the standard deviation of the betas is positive and its kurtosis value is too high. Thus, it indicates a rightly skewed cross-sectional standard deviation but its skewness is near zero, exhibiting closer distribution to the left and right of the center point.

The Jargue-Bera test does not support normal distribution for either of the variables. The p-values are statistically significant for both standard deviation and logarithms of cross-sectional standard deviation factors at 1% level.

The kurtosis values of all variables, as in logarithms of cross-sectional standard deviation and standard deviation, are positive indicating a peaked distribution rather than a flat distribution. It is expected to have skewness near zero when the data has a normal distribution. However, there is no normality for the daily data. Another indicator of that is significant p-values. Furthermore, if the data is symmetric, skewness near zero is also expected. Thus, an asymmetry is observed for these daily data. Negative skewness values of H_{mt} and β_{imt}^{b} variables report that the data is skewed left, thus, the left tail is longer than the right tail, whereas the other variables are skewed right.

Table 3 also reports that higher standard deviation value is consistent with the higher mean value of cross-sectional standard deviation of the betas. Thus, cross-sectional standard deviation has the highest standard deviation value, as expected. It indicates that this variables deviates from the average value more than the others.

3.2.2.3.2. Descriptive Statistics for Intraday Data

Descriptive statistics for the intraday data of session one market is shown in Table 4. There are 4821 observations for all variables. Similar to the daily data, the

Table 4. Descriptive Statistics of Intraday Data (Session One Market)

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jargue-Bera	Probability	Observations
log [$Std_t(\beta^b_{imt})$]	-0.424787	-0.448889	2.031967	-1.500388	0.587070	0.507719	2.473703	251.1561	0.000000	4821
H_{mt}	-0.000986	-0.000189	0.007283	-0.222542	0.005714	-21.47223	648.5563	80368734	0.000000	4821
log σ_{mt}	0.088224	0.076601	0.299843	0.017004	0.047219	1.495628	5.650572	3066.844	0.000000	4821
r_{mt}	0.001082	0.000408	0.102795	-0.126130	0.023145	0.000910	6.025820	1757.873	0.000000	4821
β^b_{imt}	1.013232	0.996775	10.54167	-9.381731	0.366228	-0.822796	324.8387	19887907	0.000000	4821
$Std_t(\beta^b_{imt})$	1.038214	0.355723	107.6383	0.031595	2.628081	18.97758	652.9943	81395169	0.000000	4821
SMB_t	-0.001728	-0.000495	0.250807	-0.497210	0.030647	-0.895330	23.21896	79106.43	0.000000	4821
HML_t	-0.000457	-1.41E-05	0.363263	-0.442382	0.045430	-0.517447	19.15494	50314.19	0.000000	4821

highest mean value is found for cross-sectional standard deviation of the betas is 1.038214, while the lowest one is found for logarithms of cross-sectional standard deviation as -0.424787. The maximum value of standard deviation is 107.6383 and the minimum value is 0.031595. The maximum value of the logarithms of cross-sectional standard deviation is 2.031967 and the minimum value is -1.500388.

When the standard deviation values of the variables are compared, highest degree is found for cross-sectional standard deviation of the betas, similar to the daily data. It means that it diverges from the average value more than the other variables.

There is a high degree of kurtosis for cross-sectional standard deviation and its skewness value is not close to zero. Hence, there is no symmetry and normality. Table 4 reports positive skewness values for logarithms of cross-sectional standard deviation, market volatility, market return, and cross-sectional standard deviation. Negative values are observed for the herding parameter H_{mt}, risk factor β^b_{imt}, and Fama-French factors of SMB_t and HML_t. While positively skewed variables indicate rightly skewed tails, negatively skewed variables are distributed to the left on a histogram. Jargue-Bera values of all variables are statistically significant at the 1% level. This is another indicator of no normality for session one market data.

Table 5 shows the descriptive statistics for all variables in session two market. The sample covers the periods from 02.01.1990 to 31.12.2014 and the results of 4903 observations are presented, on intraday basis.

The highest mean value is found for cross-sectional standard deviation of the betas as 3.208554, while the lowest one found for herding parameter H_{mt} which is -9.36E-05. The maximum value of standard deviation is 1631.667 and the minimum value is 0.035692. The maximum mean value of H_{mt} is 0.000543 and the minimum is -0.001002. These mean values are consistent with the standard deviations of the variables. The highest standard deviation is found for cross-sectional standard deviation of the betas. While it deviates from the average value more than the other variables, H_{mt} is the variable deviates at least.

Jargue-Bera statistics were significant at the 1% level, indicating no normality for all variables. For a normal distribution, skewness values also should be zero. As shown in Table 5, while standard deviation variable has highly positive skewness value indicating rightly skewed distribution, beta has highly negative skewness indicating a

Table 5. Descriptive Statistics Daily Data (Session Two Market)

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jargue-Bera	Probability	Observations
log [$Std_t(\beta^b_{imt})$]	-0.088708	-0.132766	3.212632	-1.447433	0.666875	0.269211	2.697335	74.55216	0.000000	4903
H_{mt}	-9.36E-05	-3.69E-05	0.000543	-0.001002	0.000265	-1.249524	4.285503	1543.353	0.000000	4903
log σ_{mt}	0.065725	0.058675	0.232786	0.003129	0.030057	1.488652	6.317758	3883.293	0.000000	4903
r_{mt}	0.000154	9.50E-05	0.092113	-0.105126	0.015799	-0.039935	6.903594	2979.015	0.000000	4903
β^b_{imt}	0.993337	0.992030	36.99786	-280.4282	4.246346	-61.86566	4114.865	3.31E+09	0.000000	4903
$Std_t(\beta^b_{imt})$	3.208554	0.721677	1631.667	0.035692	27.84824	50.00103	2730.421	1.46E+09	0.000000	4903
SMB_t	0.001608	0.000239	0.276416	-0.221856	0.030294	0.194282	9.555362	8427.099	0.000000	4903
HML_t	0.000740	8.17E-07	0.441885	-0.334051	0.045784	0.403584	15.52824	30799.27	0.000000	4903

distribution to the left. Other variables skewed near zero, thus, presenting closer distribution to the left and right of the center point, consistent with symmetry. Furthermore, standard deviation and beta have excess kurtosis indicating stronger peaked and flat distribution, respectively.

CHAPTER FOUR
EMPIRICAL FINDINGS AND DISCUSSION

In this chapter, empirical findings of the study is covered and then the results are discussed.

4.1. DETECTING HERD BEHAVIOR THROUGH CROSS-SECTIONAL DISPERSION OF STOCK RETURNS

In this study, the methodology based on the cross sectional dispersion of stock returns suggested by Christie and Huang (1995) and developed by Chang, Cheng and Khorana (2000) and the methodology based on the cross-sectional volatility of beta coefficients suggested by Hwang and Salmon (2004) were used to investigate herd behavior in Borsa Istanbul.

The cross sectional dispersion of stock returns is calculated by using two different methodologies: cross-sectional standard deviation of the stocks and cross-sectional absolute valuation of the stocks, as mentioned earlier.

4.1.1. Regression Results for Cross-Sectional Standard Deviation of Stock Returns

At first, regression results for cross-sectional standard deviation of stock returns are presented on daily and intraday basis.

4.1.1.1. Daily Results for Cross-Sectional Standard Deviation of Stock Returns

Following Christie and Huang (1995), regression analysis was used to examine herd behavior during up and down market movement days. Table 6 provides the daily regression results for the equation of $CSSD_t = a + \beta^D D^D{}_t + \beta^U D^U{}_t + \epsilon_t$. The coefficients of the dummy variables capture the extent of herd behavior during periods with extreme up and down market movements. The 1 % and 5 % of the lower and upper tail

Table 6. Regression Results for Cross-Sectional Standard Deviation Using Daily Stock Returns

		a	β^D	β^U	F	R^2	Adjusted R^2
$CSSD_t = a + \beta^D D^D_t + \beta^U D^U_t + \epsilon_t$.	1% criterion	0,114**	0,046**(0,769)	0,027*(1,792)	6,364*	0,0020	0,0017
	5% criterion	0,115**	0,008 (1,275)	0,002 (0,350)	0,6755	0,00021	-0,0001

t-statistic in parentheses

**Significance at 1% level

* Significance at 5% level

of the market return distribution were used to identify days with extreme market movements. BIST 100 Index was used to represent the market. If there is herd behavior in Borsa Istanbul, small dispersions are expected between stock returns and the market return.

First of all, the regression assumptions are tested to justify the use of linear regression models and daily estimated regression results are adjusted for linearity, normality, multicollinearity, autocorrelation and heteroscedasticity. After the adjustments, the included observations in the sample became 6503 for daily data.

As shown on Table 6, consistent with the study of Christie and Huang (1995), positive and statistically significant coefficients of β^D and β^U indicate that the stock returns do not herd around the market return during either down or up market movement days under the 1 % criterion. The coefficients of β^D and β^U are also positive but insignificant under the 5 % criterion indicating that CSSD do not diverge from the overall market, consistent with the absence of herding. In the presence of herding, neative and statistically significant coefficients of β^D and β^U are expected, as mentioned earlier. Thus, H_0 is supported that there is no herd behavior during up market movement days (*Hypothesis 1*) and down market movement days (*Hypothesis 2*). Hovewer, the estimates for β^D are greater than β^U under both 1% and 5% criteria indicating that the rate of dispersion is higher in the down markets than up markets. Thus, since stock returns diverge from the overall market return more in down markets, it may suggest that the tendency of herd behavior is higher in up market, even though there is no evidence of herd behavior.

In addition, the α term represents the average level of stock dispersions when the market return is zero. The values of α are positive and statistically significant for both 1 % and 5 % of the return distributions. While F value is significant at 1%, insignificant at 5% statistical level. This shows the validity of the model at 1% statistical level.

4.1.1.2. Intraday Results for Cross-Sectional Standard Deviation of Stock Returns

Table 7 provides the intraday regression results for the methodology of cross-sectional standard deviation of stock returns (CSSD) when the market is up and down. Closing prices of the stocks are obtained and logarithmic returns derived from closing prices are calculated to examine herd behavior. The closing prices of the stocks obtained from session one and session two markets are used as the closing prices of the market. The 1 % and 5 % of the lower and upper tail of the market return distribution were used to identify days with extreme market movements.

Before predicting the results of linear regression, the estimated regression coefficients are adjusted for linearity, normality, multicollinearity, autocorrelation and heteroscedasticity for the up and down market models. After the adjustments, the sample includes 4790 observations in session one market model and 4766 observations for the session two market model.

In line with the study of Christie and Huang (1995), positive coefficients of β^D and B^U are found indicating of no herding in Borsa Istanbul during extreme up and down market movement days for session one market. Negative and statistically significant coefficients are expected in the presence of herding. In other words, cross-sectional standard deviation is expected to be small between stock returns and the market return. Thus, H_0 is also accepted for session one market and it cannot be said that there is herd behavior during up (*Hypothesis 1*) markets and down (*Hypothesis 2*) markets based on these findings.

The average level of equity dispersions is 0.1259 under 1 %, and 0.1242 under 5 % criterion when the market return is zero. The cross-sectional standard deviation can be explained at a higher degree under 5% criterion than 1% criterion for market session one. F value is significant to show the validity of the model for session one market.

Table 7. Regression Results for Cross-Sectional Standard Deviation Using Intraday Stock Returns

		a	β^D	β^U	F	R^2	Adjusted R^2
Regression Results for Session One Market							
$CSSD_t = a + \beta^D D^D_t + \beta^U D^U_t + \epsilon_t$.	1% criterion	0,1259**	0,0027 (0,1100)	0,0717*(2,8706)	4,1235*	0,0032	0,0024
	5% crtierion	0,1242**	0,0037 (0,3249)	0,0447**(4,000)	7,9981**	0,0061	0,0054
Regression Results for Session Two Market							
$CSSD_t = a + \beta^D D^D_t + \beta^U D^U_t + \epsilon_t$	1% criterion	0,1327**	-0,0044 (-0,1674)	0,0305 (1,1579)	0,6863	0,0006	-0,0003
	5% criterion	0,1323**	-0,0029 (-0,2402)	0,0147 (1,2301)	0,8031	0,0007	-0,0002

t-statistic in parentheses

* Significance at 5%

**Significance at 1%

For session two market, the average levels of stock dispersions (α) are also positive and statistically significant under both 1 % and 5 % level. The results indicate that while the beta coefficients of the down markets (β^D) are negative but statistically insignificant, the beta coefficients of the up markets (β^U) are positive but statistically insignificant under both 1% and 5% criteria. These estimates of β^D and β^U show the evidence against the presence of any herd behavior. In other words, large dispersions between stock returns and market return are observed during extreme up and down market movement days, contrary to expectation. Thus, H_0 is accepted again for session two markets and it can be said that the stock returns do not diverge from session two market returns, implying no herding in up (*Hypothesis 1*) and down markets (*Hypothesis 2*). Moreover, the beta estimates of session two market are smaller than the session one markets' beta estimates. This small dispersion indicates that even if there is no herding, stock returns diverges from the market return less in session two market, by contrast with session one market. Thus, it can be concluded that tendency of herd behavior is higher in session two markets.

On the other hand, F value is insignificant to explain goodness of the model. It means that the model is not valid for the sample of session two market. However, it can be still reliable as a whole.

4.1.2. Regression Results for Cross-Sectional Absolute Valuation of Stock Returns

Regression results for cross-sectional standard deviation of stock returns are also presented on daily and intraday basis.

4.1.2.1. Daily Results for Cross-Sectional Absolute Valuation of Stock Returns

The methodology of the cross-sectional absolute valuation of the stocks (*CSAD)* was constructed as a deeper analysis to measure return dispersions. This analysis, suggested by Chang et al. (2000), facilitates the detection of herding over the entire distribution of market returns (Chiang, Li and Tan, 2010: 113). A non-linear relation is expected between the market return and stock returns in Borsa Istanbul, in the presence of herd behavior. The statistics reported in Table 8 indicate regression results on the basis of daily data.

The regression assumptions are, firstly, tested to predict linear regression models correctly and the estimated regression coefficients are adjusted for linearity, normality, multicollinearity, autocorrelation and heteroscedasticity. After the adjustments, the included observations in the sample became 6503 for the entire market model, 3287 for the up market model and 3187 for the down market model.

For the overall market, the constant variable (α) which indicates the average dispersion, is positive and statistically significant. Moreover, positive and significant coefficient of γ^1 indicates that the cross-sectional absolute valuation increases with an increase of absolute market return at the rate of 0.4674. Negative and statistically significant coefficient of γ^2 is expected as an indicator of herd behavior. However, the coefficient γ^2 is positive. This result also shows a linear relation for the entire market. Thus, there is no evidence of non-linear relation, hence no herd behavior in Borsa Istanbul, supporting the H_0 (*Hypothesis 3*). The model explains the 39.7 % of the dependent variables as given with the adjusted R-squared statistics. Moreover, according to the F-statistics of the daily model, it is seen that the model is valid at 1% level.

In both up and down markets, even if there is significant relationship between stock return dispersions and market return, positive γ^2 coefficient of both markets indicates evidence against the presence of non-linearity. This implies that CSAD does not increase at a decreasing rate. In other words, CSAD increases when the market return increases. Thus, H_0 is accepted and it can be concluded that there is no herd behavior in both up (*Hypothesis 4*) and down (*Hypothesis 5*) markets in Borsa Istanbul. Additionally, when comparing up and down market models, the rate of increase is 0.4603 in the up market, while it is 0.4791 in the down market, as reported in Table 8. This means that investors tend to herd more in up markets rather than down markets because of the smaller dispersion, consistent with the results of cross-sectional standard deviation of the stocks.

As a result, when the regressions are conducted to analyze returns dispersions under market stress days, the estimated coefficients for γ^2 are positive indicating that

Table 8. Regression Results for Cross-Sectional Absolute Valuation Using Daily Stock Returns

	α	γ_1	γ_2	F	R^2	Adjusted R^2
$CSAD_t = a + \gamma_1 \lvert R_{m,t} \rvert + \gamma_2 (R_{m,t})^2$	0,0236**	0,4674**(1,313)	4,8334**(8,004)	2.114,2**	0,3973	0,3971
$\mathrm{CSAD}_t^{\mathrm{UP}} = a + \gamma_1^{UP} \lvert R_{mt}^{UP} \rvert + \gamma_2^{UP} (R_{mt}^{UP})^2 + \epsilon_t$	0,0241	0,4603**(9,577)	4,6476**(5,761)	1.010,3**	0,3839	0,3535
$\mathrm{CSAD}_t^{\mathrm{DOWN}} = a + \gamma_1^{DOWN} \lvert R_{mt}^{DOWN} \rvert + \gamma_2^{DOWN} (R_{mt}^{DOWN})^2 + \epsilon_t$	0,0229**	0,4791**(9,454)	4,9616**(5,724)	1.108,42**	0,4138	0,4135

t-statistic in parentheses

* Significance at 5%

**Significance at 1%

there is no evidence of herd behavior for both up and down markets by using daily stock returns. Even if herding is not observed for both up and down markets, larger dispersion from the average market return indicates the probability of less herding for down markets, as similar with the result of Table 6.

The R-squared value shows that 35% and 41% of the variation in cross-sectional absolute valuations can be explained by daily market returns and squared term for both up and down markets, respectively. Furthermore, F values of up and down market models are significant enough to indicate validity of the models.

4.1.2.2. Intraday Results for Cross-Sectional Absolute Valuation of Stock Returns

The methodology of cross-sectional absolute valuation of stock returns was used as an extended analysis to measure whether there is a linear relation or not between stock returns and the market return. It is expected that the relation is non-linear in the presence of herding. The statistics reported in Table 9 are based on the intraday data with the returns reported as session one and session two markets.

The estimated regression coefficients are, firstly, adjusted for linearity, normality, multicollinearity, autocorrelation and heteroscedasticity. After the adjustments, the results of linear regression are evaluated. After the adjustments, the included observations are 4790 for the entire market model, 2619 for the up market model and 2174 for the down market model in session one market, 4766 for the entire market model, 2402 for the up market model and 2364 for the down market model in session two market.

For session one market, the equation of $CSAD_t = a + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t})^2$ shows the results. The constant variable (a) is positive and statistically significant. Positive and significant coefficient of γ^1 indicates that stock dispersions increase when absolute market return increases. Positive and statistically significant coefficient of γ^2 provides evidence of linearity. Thus, H_0 is accepted and it can be said that stock returns diverge from the market return, hence indicating no herd behavior (*Hypothesis 3*), as in cross-sectional standard deviation method.

Table 9. Regression Coefficients for Cross-Sectional Absolute Valuation Using Intraday Stock Returns

	α	γ_1	γ_2	F	R^2	Adjusted R^2
Regression Results for Session One Market						
$CSAD_t = a + \gamma_1\lvert R_{m,t}\rvert + \gamma_2(R_{m,t})^2$	0,0233**	0,5398** (9,8939)	4,9776** (5,8586)	5,8990**	0,3142	0,3137
$CSAD_t^{UP} = a + \gamma_1^{UP}\lvert R_{mt}^{UP}\rvert + \gamma_2^{UP}(R_{mt}^{UP})^2 + \epsilon_t$	0,0233**	0,5378** (9,844)	5,000** (5,535)	589.01**	0,3140	0,3134
$CSAD_t^{DOWN} = a + \gamma_1^{DOWN}\lvert R_{mt}^{DOWN}\rvert + \gamma_2^{DOWN}(R_{mt}^{DOWN})^2 + \epsilon_t$	0,0260**	0,5136** (4,1960)	3,6735* (2,4693)	1,4747**	0,4559	0,4528
Regression Results for Session Two Market						
$CSAD_t = a + \gamma_1\lvert R_{m,t}\rvert + \gamma_2(R_{m,t})^2$	0,0245**	0,4904** (8,1588)	5,2700** (4,7014)	3,9540**	0,2507	0,2501
$CSAD_t^{UP} = a + \gamma_1^{UP}\lvert R_{mt}^{UP}\rvert + \gamma_2^{UP}(R_{mt}^{UP})^2 + \epsilon_t$	0,0245**	0,4913** (8,1748)	5,1958** (4,6282)	3,893**	0,2479	0,2473
$CSAD_t^{DOWN} = a + \gamma_1^{DOWN}\lvert R_{mt}^{DOWN}\rvert + \gamma_2^{DOWN}(R_{mt}^{DOWN})^2 + \epsilon_t$	0,0233**	0,5565** (10,6397)	4,014** (4,8785)	398.87**	0,2560	0,2554

t-statistic in parentheses

* Significance at 5%

**Significance at 1%

When the market is up, the relation between cross-sectional absolute valuation and the squared market return (γ^2) is positive and also significant at the level of 1% pointing to absence of herd behavior in session one market. Similar with the up market, the coefficient of γ^2 for down market of session one is also positive and significant implying evidence against the herd behavior. Positive and significant coefficient of the absolute market return indicates a linear relationship between stock market returns and their dispersions during up and down extreme market movement days. Thus, H_0 can be accepted that there is no herd behavior if the relation between market return and stock dispersion is linear during up (*Hypothesis 4*) and down (*Hypothesis 5*) market movement days in session one market.

According to the adjusted R-squared statistics, the model explains the 31 % of the dependent variable. Furthermore, the R-squared values are 31% for up market and 45% for down market. As seen, the down market model explains the variation in cross-sectional absolute valuations at a higher degree than up market model. The models are valid at 1% significance on the basis of F value.

The statistics reported in Table 9 also indicate the results for session two market. The equation of $CSAD_t = a + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t})^2$ provides regression results for the entire market of session two. Positive and significant coefficient of γ^1 indicates that the cross-sectional absolute valuation of the stock returns increases with an increase in the average market return at the rate of 0.4904. Positive coefficient of γ^2 is not an indication of non-linear relation between cross-sectional absolute valuation and the average market return. It suggests that cross-sectional absolute valuation does not increase at a decreasing rate when the average market return increases hence providing evidence against the herd behavior. The constant value (*a*) is also positive and significant. Thus, H_0 is accepted that there is no herd behavior if the relation between market return and stock dispersion is linear in session two market (*Hypothesis 3*).

The adjusted R-squared value shows that 25% of cross- sectional absolute valuation can be explained by using intraday market return of session two. F value is statistically significant at the 1% level, thus, the model is valid.

Table 9 exhibits the regression results for up and down market models in session two market by using cross-sectional absolute valuation of the stock returns (CSAD). Similar with the market session one, positive value of γ^1 indicates that absolute market returns increase with CSAD. The relation between cross-sectional absolute valuation and the squared market return (γ^2) is also positive and significant suggesting the linearity and absence of herd behavior under the up and down market conditions. Thus, H_0 is supported that there is no herd behavior if the relation between market return and stock dispersion is linear during up (*Hypothesis 4*) and down (*Hypothesis 5*) market movement days in session two market.

The adjusted R-squared values of two models are very close. F values of the models for up and down markets are significant enough to explain goodness of the model.

4.2. DETECTING HERD BEHAVIOR THROUGH CROSS-SECTIONAL VOLATILITY OF BETA COEFFICIENTS

The methodology based on the cross-sectional volatility of beta coefficients suggested by Hwang and Salmon (2004) were used to investigate herd behavior in Borsa Istanbul.

4.2.1. Daily Regression Results for Cross-Sectional Volatility of Beta Coefficients

Cross-Sectional Volatility of Beta Coefficients suggested by Hwang and Salmon (2004) has also been employed to investigate herd behavior in Borsa Istanbul.

Table 10 provides the regression results for the equations of three state-space models, which were explained in the second chapter, on daily basis. To be used in state-space models, firstly, beta coefficients are estimated and then cross-sectional volatility of beta coefficients is calculated.

Model 1 reported in Table 10 exhibits findings of the equation of $log\ [Std_c\ (\beta^b_{imt})] = \mu_m + H_{mt} + v_{mt}$. Model 2 includes market volatility and market return variables ($log\ [Std_c\ (\beta^b_{imt})] = \mu_m + H_{mt} + c_{m1}\ log\ \sigma_{mt} + c_{m2}\ r_{mt} + v_{mt}$). The results of the equation of $log\ [Std_c\ (\beta^b_{imt})] = \mu_m + H_{mt} + c_{m1}\ log\ \sigma_{mt} + c_{m2}\ r_{mt} + c_{m3} SMB_t + c_{m4} HML_t + \nu_{mt}$ are also reported as Model 3, in Table 10[5].

Before predicting the estimated regression coefficients, they are adjusted for linearity, normality, multicollinearity, autocorrelation and heteroscedasticity for three models presented in Table 10. After the adjustments, the sample includes 6503 observations for daily data.

Model 1 indicates significant coefficient of σ_{mn}, supporting the existence of herd behavior at a rate of 51% towards the market portfolio. Thus, H_0 is rejected for overall market (*Hypothesis 6*). According to the signal-proportion value[6], herding also explains around 50% of the total variability in cross-sectional volatility of beta coefficients. F value verifies the validity of the model at the 1% significance.

The other results which are adjusted for the assumptions of linear regression are reported for model 2. Model 2 reports stronger evidence of herd behavior when the market volatility and the market return are taken into account. Hwang and Salmon (2004: 23) explain that significant coefficient of herding (σ_{mn}) is not enough to indicate herd behavior, but the herding level can be examined given the state of the market. Thus, the herding coefficient of σ_{mn} is expected to be close to 1 for the high levels of herding. For instance, if σ_{mn}=1, there is perfect herding.

In addition, when the market volatility and the market return are added to the model, the coefficient of herding is still significant. This result shows that the changes in the cross-sectional volatility of beta coefficients could be explained by intentional herding rather than changes in these fundamentals. In other words, investors do not herd because of publicly known changes in market fundamentals. Thus, it can be argued that they herd intentionally in Borsa Istanbul rejecting H_0 (*Hypothesis 7*). It is also seen that when the market return increases, the cross-sectional volatility of beta coefficients decreases, indicating higher tendency of herding in up markets.

As presented in Model 3, size and value factors, which are derived from The Fama-French Factor Model, were added to the equation. The higher herding level

[5] These models were explained in the second chapter, in detail.

[6] Proportion of Signal value is calculated by dividing the σ_{mn} by the time series standard deviation of the logarithmic cross-sectional standard deviation of the betas, which according to Hwang and Salmon (2004) indicates what proportion of the cross-sectional volatility of the betas is explained by herding (Gavriilidis et al., 2013: 19).

Table 10. Regression Results of State-Space Models Using Daily Stock Returns

	σ_{mn}	c_{m1}	c_{m2}	c_{m3}	c_{m4}	F	Proportion of Signal
Model 1	0,51111 (101.3)**	-	-	-	-	10261.15**	0.5046
Model 2	0.6055 (112.7)**	-0.5559 (-32.3)**	-0.0147(-2.3)*	-	-	4491.65**	0.5373
Model 3	0.8651 (198.0)**	-0.3250 (-25.6)**	0.0004(0.1)	0.0269 (7.9)**	-0.0430 (-17.6)**	7976.04**	0.4369

t-statistic in parentheses

* Significance at 5%

**Significance at 1%

(86.51%) is found. The coefficient of σ_{mn} is still significant indicating an intentional herding and thus *H₀* is rejected again for overall market (*Hypothesis 7*). There is a linear relationship between the size factor (SMB) and the cross-sectional standard deviation of the betas. When the firm size increases, the cross-sectional standard deviation increases and thus, herding decreases. Negative and statistically significant coefficient of book-to-market ratio (HML) also indicates that it increases with decreases of the cross-sectional standard deviation, as expected. Because higher book-to-market value may be an indicator of smaller firm size. While firm size (SML) decreases, herding increases, as stated earlier.

F values indicate that the models are valid at the level of 1%. Total variability in cross-sectional volatility of beta coefficients is explained by herding at a rate of 53.73% for model 2 and 43.69% for model 3, as given with signal-proportion values.

4.2.2. Intraday Regression Results for Cross-Sectional Volatility of Beta Coefficients

Table 11 reports the results which are adjusted for linearity, normality, multicollinearity, autocorrelation and heteroscedasticity based on intraday data of session one and session two market. After the adjustments, there are 4785 observations in session one market and 4771 observations in session two market.

According to coefficients of σ_{mn}, herd behavior is found for three of the models but the level of herding shows a minor difference in session one market. Thus, H_0 is rejected and it can be said that there is herd behavior among investors in session one market (*Hypothesis 6*). Additionally, when variables of market volatility, market return, size and value factors are included, there is still significant σ_{mn}, implying intentional herding rather spurious rejecting H_0 of the sub-hypothesis (*Hypothesis 7*).

Comparable with the results of Model 2 in Table 10, when the market volatility decreases, the cross-sectional standard deviation of beta coefficients increases. Model 3 reports the regression results under Fama-French Model as well as CAPM. However, while no significance is found for SML factor, negative and significant coefficient is found for HML factor. Non-linear relation shows that when HML factor increases, the cross-sectional standard deviation of the betas decreases and herding increases.

Table 11. Regression Results of State-Space Models for Herd Behavior Using Intraday Stock Returns

	σ_{mn}	c_{m1}	c_{m2}	c_{m3}	c_{m4}	F	Proportion of Signal
			Regression Results for Session One Market				
Model 1	0.4794 (86.7)**	-	-	-	-	7519.584**	0.5529
Model 2	0.5576 (93.4)**	-0.4315 (-23.6)**	-0.0559 (-8.3)**	-	-	3086.398**	0.5970
Model 3	0.5570 (91.7)**	-0.4171 (-22.1)**	-0.0572 (-8.4)**	0.0011 (0.2)	-0.0144 (-3.8)**	1791.689**	0.6074
			Regression Results for Session Two Market				
Model 1	0.8304 (177.8)**	-	-	-	-	31621.23**	0.4670
Model 2	0.8542 (193.3)**	-0.3448 (-26.6)**	0.0012 (0.26)	-	-	12528.21**	0.4419
Model 3	0.8651 (198.0)**	-0.3250 (-25.6)**	0.0004(0.1)	0.0269 (7.9)**	-0.0430 (-17.6)**	7976.04**	0.4369

t-statistic in parentheses

* Significance at 5%

**Significance at 1%

F value verifies the validity of the three state-space models at the 1% significance. Signal-proportion values indicates that the cross-sectional volatility of the beta coefficients is explained by herding at a rate of 55.29%, 59.70% and 60.74% for model 1, mode 2 and model 3, respectively.

The results of three state-space models for session two market are also presented in Table 11. By contrast with the results of session one market, the table indicates the existence of herd behavior at a higher degree of above 80% for three of the models. Thus, H_0 is rejected again for session two market (*Hypothesis 6*). This result is consistent with the result of cross-sectional dispersion of the stocks. Additionally, when market fundaments are taken into consideration, the significance of herding does not change. It can be said that H_1 is accepted and there is an intentional herding in session two market in Borsa Istanbul (*Hypothesis 7*).

Moreover, when market volatility increases, the cross-sectional standard deviation of beta coefficients decreases, as in the session one market. Additionally, insignificant coefficient of the market return shows that there is no relationship between the market return and the cross-sectional standard deviation of beta coefficients. SMB and HML coefficients are significant at 1% level. It can be concluded that herding is lower in firms which have higher sizes. Herding explains around 46.7%, 44.19% and 43.69% of the total variability in cross-sectional volatility of beta coefficients. The model is valid because of the significance of F value at the 1% level.

4.3. DISCUSSION

4.3.1. General Discussion

In this study, herd behavior is investigated in Borsa Istanbul in terms of cross-sectional dispersion of the stock returns and cross-sectional volatility of the beta coefficients covering an extensive period from 1988 to 2014.

The existence of herding, at first, is measured in up and down markets based on the cross-sectional standard deviation of the stocks. According to regression results, herd behavior among investors is not found for either up or down market movement days. These results are consistent with the studies of Altay (2008), Coban (2009) and Dogukanlı and Ergun (2011) which are conducted to Borsa Istanbul.

As an extended analysis, the existence of herd behavior is also investigated basen on the cross-sectional absolute valuation of the stocks in Borsa Istanbul and a non-linear relation between the cross-sectional absolute valuation and the market return is expected in the presence of herding. However, a linear relation is found not supporting the presence of herding in Borsa Istanbul. Thus, it can be argued that investors may prefer to decide based on their own beliefs rather than follow the others' decisions in Borsa Istanbul. These results are consistent with the assumptions of efficient market hypothesis and investors may behave rationally.

A different methodology based on the cross-sectional volatility of the betas, suggested by Hwang and Salmon (2004) is also conducted to measure herd behavior in Borsa Istanbul and as a result, herd behavior is found. The existence of herding may be correlated with the effect of beta. Because, beta may be a better parameter than squares of market return to explain stock returns, as stated earlier.

Although there was no evidence of herd behavior in up and down markets, the coefficients of up markets are lower in contrast with down markets based on the results of cross-sectional dispersion of the stocks. This result may be interpreted as the stock returns diverging from the market index less and thus investors may have the tendency to herd more in up markets in comparison with the down markets, since a smaller dispersion is expected between stocks returns and market index in the presence of herding, as Christie and Huang (1995) stated. The results of the methodology based on the cross-sectional volatility of the betas also support the existence of stronger tendency for herding in up markets because the coefficient of market return is negative indicating the non-linearity between the market return and cross-sectional dispersion of the betas. Thus, it can be said that when the market return increases, standard deviation decreases and herding increases.

In addition, both of the methodologies are conducted to measure herd behavior in session one and session two markets. The results of the methodology based on stock dispersions indicate no herd behavior on the basis of intraday returns. However, herding is found by using the cross-sectional volatility of the betas in both session one and session two markets. When the results of session one and session two markets are compared, it is seen that although the volatility is lower, the herding level is higher in session two market in Borsa Istanbul.

The methodology developed by Hwang and Salmon (2004) also provides to investigate whether herd behavior is intentional or not in the presence of herding. Because investors do not always follow the market trend because of observing the others. They may act in the same way in response to the publicly announcements. Market volatility, market return, size and value factors are included to differentiate intentional herding from spurious herding and an intentional herding is found among investors in Borsa Istanbul.

4.3.2. Herding and Market Volatility

As stated earlier, no herding is observed in up and down markets but the tendency of herd behavior is higher when the market is up. Lower volatility may be the reason of higher herding during up market days. Blasco, Corredor and Ferreruela (2012: 15) argue that investors' behavior has a greater influence on volatility during extreme down market days which can be considered extreme falls. They may not believe the information which they heard from the others during these volatile days and they may avoid to follow the others. Thus, the possibility of herding decreases. Under these circumstances, higher herding found in up markets is an expected result, in contrast with down markets. This result is consistent with the suggestions of Hwang and Salmon (2004). They argue that investors turn to their fundamentals and prefer to decide based on their own beliefs rather than to herd during these volatile days.

The same argument can be true for the session two markets because of the lower volatility in contrast with session one markets, as found in this study. Guner and Onder (2012) state that there is uncertain information and rumor at the beginning of the session one market. Stoll and Whaley (1990) explain this uncertainty that price makers have more information, so they manipulate and affect the price to their benefits. Thus, the competitiveness decreases and the volatility increases. Madhavan, Richardson and Roomans (1997) explain the higher volatility in the opening session that the ambiguity which emerges when the market is closed is reflected to the prices. As a result, increased volatility with this ambiguity causes investors to avoid herding in session one market. During the day, the volatility decreases and the market becomes stable. The stability of session two market induces investors to herd more because of their confidence about the future direction of the market. From the results of this study, it is actually seen that while the volatility is lower, herding is higher in session two market, as reported in Table 11.

4.3.3. Herding, Firm Size and Growth Value

Cross-sectional volatility of the betas method enables to evaluate herd behavior in Borsa Istanbul in terms of firm size and values. When these variables are added to the model, significant σ_{mn} (herding parameter) is expected in the presence of intentional herding. In this study, there is an evidence of intentional herding.

Positive coefficient of size (market capitalization) indicates a linear relation between firm size and cross-sectional dispersion. Thus, when market capitalization increases, cross-sectional dispersion also increases and herding decreases. Thus, a strong evidence (at a rate of 86.51%) is found that investors imitate the others on small size firms in contrast with big size firms in Borsa Istanbul. Because, to gather information about them is difficult (Bikhchandani and Sharma, 2000: 25). Investors may not prefer to take risk for small size firms and move in the same direction with the others. Merli and Roger (2013) support this finding that investors tend to disregard their own decisions, and observe what the others do, for firms which have small capitalization.

This herding in small size firms is also consistent with agency model of Scharfstein and Stein (1990). Accordingly, investors cluster in groups when selling small stocks which have poor past performance but hold on to stocks with large capitalization without regarding of their past performance.

The negative coefficient of value factor also shows that evidence of herding appears strong for high-growth stocks in Borsa Istanbul, as well as small stocks. Because when value increases, standard deviation decreases and thus herding increases. This result is consistent with the results of Wermers (1999). Accordingly, investors exhibit high levels of herding in high growth stocks such as the stocks with small capitalization.

4.3.4. Herding and Overconfidence

Herd behavior found under normal market conditions rather than noisy market conditions can also be explained by confidence of investors. Investors may lose their confidence about the future under uncertain and risky market conditions. Thus, lower confidence may lead them to turn to their fundamentals rather than herd, as stated by Hwang and Salmon (2004: 587). This may also be an explanation of the findings of no herding in up and down market movement days in Borsa Istanbul.

However, it is found that investors tend to herd more in up markets, as stated earlier. As explained in Seetharam and Britten (2013: 95-96), this may be due to the quick reaction of investors to negative macroeconomic news in down markets. They may not feel safe and try to behave more rationally because of loss in their confidence about the future. Thus, they may be prone to turn to their fundamentals in the presence of bleak outcomes not to decide wrong. In contrast, positive outcomes, emerged in up markets, give investors the confidence about the future of the market. Thus, they follow the market trend more in up markets.

The existence of herding found by the methodology based on the cross-sectional volatility of the betas may also indicate the existence of inexperienced investors in Borsa Istanbul. Inexperienced investors would be more overconfident and would take more risk. On the contrary, experienced investors tend to avoid risk and this may be explained by a lower degree of overconfidence (Brozynski et. al., 2004: 1). Thus, it can be said that overconfidence would decrease with experience. In the absence of overconfidence, experienced investors have a lower incentive to herd and they do not make decisions following the other investors (Odean, 1998; Chevalier and Ellison, 1999; Avery and Chevalier, 1999).

This is also related with investors' reputation. Reputation of younger and inexperienced investors is more important than experienced ones thus they herd more to earn or not to lose their reputation (Campenhout and Verhestraeten, 2010: 10). Therefore, it can be said that observed herding may be an indicator of the presence of young and inexperienced investors in Borsa Istanbul.

4.3.5. Herding Among Individual and Institutional Investors

Nofsinger and Sias (1999), and Ohlson (2010) suggest that institutional investors herd more than individual investors, because they are able to reach more private information about other investors. Thus, they affect stock market returns more than individual investors do due to larger order sizes. In line with this argument, it may be suggested that the number of institutional investors may be sufficient to affect the market in Borsa Istanbul.

On the other hand, another suggestion is that market makers, who set and update the prices, may have a great effect on investors in Borsa Istanbul. They are expected to prevent large price movements which may occur as a result of short term price imbalances in stocks and they should promote efficient markets[7]. As a matter of fact, they are mostly institutional investors who have larger impacts on the stock returns. They manage the markets, and affect the prices. Thus, they may manipulate the prices to their benefits. This manipulation leads to inefficient markets. Investors may observe the actions of these market makers in Borsa Istanbul and an intentional herding arises. Therefore, some of these market makers traded in Borsa Istanbul have

[7] See http://www.borsaistanbul.com/en/products-and-markets/markets/equity-market/market-making (05.06.2015)

foreign ownership[8]. Thus, the effect of foreign investors may be observed in Borsa Istanbul.

4.3.6. Herding Among Financial Analysts

It can also be mentioned about the effect of financial analysts on herding. They are intermediaries in financial markets who forecast earnings, and make recommendations. They collect and analyze public and private information better (Campenhout and Verhestraeten, 2010: 2). Sharma (2010: 119) reports that investors care about the recommendations of analysts. This may lead to investors to receive same correlated information with the others who listen to financial analysts. When they act accordingly, herding may arise naturally.

Moreover, Bikhchandani and Sharma (2000: 23) have mentioned that investors act based on the news letters, because they are easily observable. In line with this argument, investors may herd by looking at the news letters or other media instruments because of their fertile ground for herding. Short-term severe changes occurred in the economy and political instability in Turkey can be followed from these instruments easily. Hence, this leads investors to herd more in Borsa Istanbul because of easily collected correlated information signals from the financial analysts, newsletters or other media instruments.

4.3.7. Herding In Developing and Developed Markets

Many researchers have proved that investors herd more in developing markets than developed markets (Christie and Huang, 1995; Wermers, 1999; Chang et. Al.; Chen et al., 2003; Hwang and Salmon, 2004).

Chen, Rui, Xu (2003) argue that low availability and accuracy of information are the reasons of herding in the developing stock markets. Furthermore, severe and unexpected movements may emerge because of the political and economic instability in developing stock markets.

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[8] See market maker members http://www.borsaistanbul.com/en/products-and-markets/markets/equity-market/market-making (05.06.2015)

The results of this study indicates consistency with the argument of that investors may tend to follow the market trend in Borsa Istanbul which is a developing market. Wang (2008) states that gathering information is difficult and expensive in developing markets, instead, observing and imitating other investors' decision or the market index is relatively cheap and easy.

Additionally, Bikhchandani and Sharma (2000: 25) states that herding is observed more in developing countries because of the effect of foreign investors. Because herding by foreign investors leads to markets to be more volatile due to the capital flows in developing countries. Thus, the effect of foreign investors may also be observed in Borsa Istanbul.

4.3.8. Implications for Investors

It can be concluded from the study that daily returns diverge from the overall market return more than intraday returns. The findings of the study suggest that more herding is observed on the basis of intraday data in Borsa Istanbul. This result is consistent with the suggestions of Christie and Huang (1995) that herd behavior exhibits a short term structure. Moreover, the evidence is supported by Altay (2008). He has analyzed herding by using monthly returns in Borsa Istanbul and could not find any herding.

On the other hand, when investors herd on a stock, mispricing may arise. For instance, if investors buy the same stock because of observing others, the price of this stock will increase for a short-term period but that does not reflect its fundamental value. This mispricing will be temporary in the presence of herding. The stock price reaches a certain level, when traders will realize it is not worthwhile to herd any more, and the asset price will eventually come to its fundamental value. Until, the price reaches to its fundamental value, this mispricing will not be realized by investors, and thus it will almost be impossible to take advantage of arbitrage activities for a while.

To exploit this mispricing which occurs due to herding, an important implication for investors is to invest in stocks for a long-term unlike short-term structure of herding. They may avoid to react quickly to economic fluctuations. It provides opportunity to observe the market and may prevent investors from acting irrationally. It may be more difficult to make profits in short term, especially for small investors, in developing markets such as Borsa Istanbul.

4.3.9. Implications for Policy Makers

There may be effects of market makers in Borsa Istanbul, as stated earlier. They may affect the stock prices to their benefits, contrary to what they are supposed to do. For example, they may direct investors to certain stocks which are more profitable for them rather than investors. Therefore, the prices of the stocks, which they direct and investors trade on, increase and hence mispricing arises in short term. On the other hand, publicity about market makers and their press releases of them may cause the manipulation on the market. Therefore, investors may herd as a result of market makers' manipulation of the market.

Enforcement of regulations may be revised or increased to prevent market makers to manipulate the market and investors. This provides to reach correct information easily leading to efficient markets.

4.3.10. Implications for Investment Managers

As stated earlier, one of the forces of intentional herding is compensation plans for managers. If these compensations are designed better for managers, this makes institutions more transparent. Thus, in transparent conditions, investors may not be worried about their future and may analyze investment opportunities more rationally and this leads markets to be more efficient. This behavior reflects the reaction to publicly available information. Mispricing is prevented and prices can be close to their fundamental values in the existence of greater transparency in the markets. Even if herding is still found after having better information because of transparency, this herding may not be an intentional herding.

Table 12 reports summary of the results. The result of each hypothesis is presented based on overall market, session one market and session two market. Whereas X indicates the absence of herding, ✓ indicates the presence of herding.

Table 12. Summary Results of the Study

Methodology	Hypothesis	Overall Market	Session One Market	Session Two Market
Cross-Sectional Standard Deviation of the Stocks	There is herd behavior during up market movement days in Borsa Istanbul	X	X	X
	There is herd behavior during down market movement days in Borsa Istanbul	X	X	X
Cross-Sectional Absolute Valuation of the Stocks	There is herd behavior if the relation between market return and stock dispersion is not linear in Borsa Istanbul	X	X	X
	There is herd behavior if the relation between market return and stock dispersion is not linear during up markets in Borsa Istanbul	X	X	X
	There is herd behavior if the relation between market return and stock dispersion is not linear during down markets in Borsa Istanbul	X	X	X
Cross-Sectional Volatility of the Betas	There is herd behavior in Borsa Istanbul	✓	✓	✓
	There is an intentional herd behavior in Borsa Istanbul	✓	✓	✓

CONCLUSION

In the traditional approach, efficient market hypothesis was widely accepted in finance literature. This hypothesis assumes that investors behave rationally and it is difficult to have abnormal returns. In the 1980s, researchers have focused on the investor psychology because of the unexpected market events which cannot be explained by traditional finance. In this behavioral approach, investors are assumed not to be fully rational and they are affected by their beliefs and emotions.

In this study, herd behavior is investigated in Borsa Istanbul by using daily and intraday stock returns. While the daily data covers the period from 1988 to 2014, intraday data starts from 2nd January 1995. Thus, the sample enables to compare both daily returns with the intraday returns and session one market returns with session two market returns. The data of the market return is collected from BIST 100 Index in Borsa Istanbul. There are 6417 daily observations and 9559 intraday observations for Borsa Istanbul. The sample size increases from 47 firms in 1988 to 441 firms in 2014.

Three different methodologies are used to detect herd behavior. The first methodology of cross-sectional standard deviation of stock returns aims to investigate return dispersions during extreme up and down market movement days. These days are captured by dummy variables and then regression analyses is conducted to test herd behavior. The results of regression analysis indicates that there is no herd behavior during extreme market movement days. Thus, the cross-sectional standard deviation of stock returns do not diverge from the overall market. However, even if there is no herding for up and down markets, lower coefficient of up markets indicates that stock returns diverge from the market index less and hence investors tend to herd more in up markets in contrast with down markets (Christie and Huang, 1995). When the model is analyzed by using the intraday data, the absence of herding is still valid for both session one and session two markets. This may be an indicator of rationality of investors in Borsa Istanbul. This rationality may provide investors to decide based on their own beliefs rather than following the others. While these results are consistent with the assumptions of efficient market hypothesis, they contradict with the assumptions of herd behavior.

Extended cross-sectional absolute valuation model captures the non-linear relation between stock dispersions and market return. It is expected that if the relation is non-linear, there is herd behavior in Borsa Istanbul. However, a linear relation is found indicating the absence of herding. When compared the results of up and down market models, higher coefficients of down markets also support the view that stock returns deviate more from the overall market return and investors tend to herd less in down markets in comparison with the up markets.

The methodology based on the cross-sectional volatility of beta coefficients suggested by Hwang and Salmon (2004) is also used to detect herd behavior in Borsa Istanbul. Through this model, herding is expected to be observed under not only extreme but also normal market conditions. In the presence of herding, this model provides opportunity to determine whether herd behavior is intentional or not in Borsa Istanbul by using market volatility, market return, size and value factors. The results indicate that the higher herding level is reported in session two markets in contrast with the session one markets. Furthermore, the existence of intentional herding is found by using both daily and intraday intervals.

This study is the first comprehensive attempt to measure herding in terms of market volatility, market return, size and book-to-market ratio factors in Borsa Istanbul. This study also contributes to the international literature in the field of behavioral finance by measuring similar variables that were used in the earlier studies and strengthening their theoretical and empirical frameworks, to the best knowledge of the researcher. Furthermore, this is the first study that investigates herding covering such an extensive period (1988-2014) and compares daily and intraday stock returns to evaluate herd behavior in Borsa Istanbul.

Low volatility may be one of the reasons of herd behavior. Investors prefer to follow the market trend when the market is not volatile in Borsa Istanbul. They do not trust other investors' decisions and decide based on their own beliefs during these uncertain and volatile market conditions, as Hwang and Salmon (2004) argued. This can explain why herding is found more in session two markets in contrast with session one markets. Researchers state that session one market is more volatile and this higher volatility causes investors to avoid herding. During the day, the market becomes stable. The stability of session two market induces investors to herd more because of their confidence about the future direction of the market (Stoll and Whaley, 1990; Madhavan, Richardson and Roomans, 1997; Guner and Onder, 2002).

The effect of volatility can also be argued for up and down markets. As stated earlier, the tendency of herding among investors is more in up markets than down markets in Borsa Istanbul. Increased volatility and uncertainty in down markets may decrease the possibility of herding, consistent with arguments of the study of Hwang and Salmon (2004). In contrast, positive values in up markets give confidence to investors about the future performance of the market. Thus, they follow the market trend more in up markets. As a result, the volatility would be higher when the investors are less confident about their evaluation of the market, and would be lower when the investors are more confident, and thereby herding is a distorting phenomenon to the market efficiency.

The results of the study also show that herd behavior is observed more on the stocks with small capitalization in Borsa Istanbul. Bikhchandani and Sharma (2000) state that investors avoid risk for small size firms because of the difficulty of gathering information about them.

Herding can also be explained by information acquisition during market stress days in Borsa Istanbul. Wang (2008) states that gathering information is difficult and expensive in developing markets, instead, observing and imitating other investors' decision or the market index is relatively cheap and easy. Thus, investors tend to follow the market trend in Borsa Istanbul which is a developing market.

Moreover, institutional investors herd more than individual investors, because they are able to reach more information about other investors and they affect stock market returns more than individual investors do. In line with this argument, it can be said that there may be sufficient institutional investors to affect stock prices in Borsa Istanbul.

Market makers, which are mostly institutional investors, may manipulate stock prices and may lead markets to inefficiency. Because they may direct investors to their benefits. Investors may also herd based on the correlated information signals of financial analysts who forecast earnings and make recommendations for investors. Because of the economic and political instability in Borsa Istanbul, newsletters or other media instruments may also be followed by investors, especially who do not collect information easily. Researchers also argue that domestic investors follow the foreign investors. This may be valid in Borsa Istanbul because it is found that there is an intentional herding among investors.

There are two limitations of this study. Firstly, macroeconomic variables could not be added to the model. Because daily data of these variables is not available in the website of Central Bank of Turkey. The other limitation of the study is that the direction of herding could not be measured. There are two reasons. Firstly, it is not possible to find it by using the methodologies based on the cross-sectional dispersion of the stocks and the cross-sectional volatility of the betas. The other reason is that there is no clear distinction of investor types in the website of Borsa Istanbul. Because, it is not possible to determine which investors are institutional and which are not, and thus, it could not be reached clearly whether the individual investors follow the institutional investors or not.

For further studies, it would be suggested to incorporate macroeconomic variables to evaluate herd behavior among investors. This provides a more comprehensive analysis to evaluate changes in herding levels in Borsa Istanbul. This study does not take into account herd behavior towards these variables.

Moreover, Lakonishok, Shleifer and Vishny (LSV) Measure can be used to test the existence of herding in further studies. It would provide to determine the direction of herd behavior. Although there is no distinction between institutional and individual investors, breakdown of monthly traded values of customer, fund and portfolios are reported in Borsa Istanbul. Daily breakdowns of them can also be requested from Borsa Istanbul. Furthermore, the direction of herding between domestic and foreign investors can be investigated based on their traded values in Borsa Istanbul.

As stated earlier, it is found that investors tend to herd less during market stress days in Borsa Istanbul. Up and down markets and session one and session two markets are compared in this study to evaluate herding under risky market conditions. Consistently, Hwang and Salmon (2004) state that the crisis has contributed to a reduction in herding and is clearly identified as a turning point in herd behavior. Therefore, crisis periods can be determined and taken into consideration as sub-periods to test the effect of crisis on herding behavior among investors in Borsa Istanbul.

At last, it is predicted that marker makers may have a great effect on investors in Borsa Istanbul. For a further research, market makers, which are listed on the website of Borsa Istanbul, can be separated from the other investors and then it can be investigated whether investors follow market makers or not. Furthermore, to test the effect of market makers, analysis can be conducted to each sector. The different herding levels at the sectors can provide information on which sectors herding is more valid in different periods and whether there is an effect or direction of market makers on this herding activity or not.

Overall, even if there is no herding in Borsa Istanbul based on the stock dispersions, an intentional herding is found based on the cross-sectional volatility of the betas. Intentional herding, found in Borsa Istanbul, may provide an evidence of inefficiency. Therefore, short-term imbalances and mispricing may occur. With economic and political instability in addition to this mispricing, to reach correct information becomes more difficult and expensive. To exploit this mispricing which occurs due to herding, an important implication for investors is to invest in stocks for a long term unlike short-term structure of herding and to avoid quick reactions to economic fluctuations.

In addition, one of the reasons of intentional herding is compensation of managers, as stated earlier. This leads them to behave irrationally. If these compensations are designed better for managers, this makes institutions more transparent. Mispricing is prevented and prices can be close to their fundamental values in the existence of transparency.

To exploit this mispricing and gather information easily, one implication can be suggested for policy makers. Enforcement of regulations may be revised or increased for market makers to prevent large price movements which may occur as a result of short term price imbalances in stocks. Because their direction to investors and their press releases may cause the manipulation of the market and thus herding may arise.

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APPENDIX

APPENDIX 1: Kalman Filter

The Kalman Filter is suggested by Kalman (1960) and developed by Kalman and Bucy (1961). The aim of this filter is to minimize the mean square error of estimated parameters.

The state space model is explained by using Kalman Filter with two equations:

$$Y_t = c + SX_t + \varepsilon_t$$

$$X_t = d + HX_{t-1} + z_t$$

where Y_t is the measurement equation at time t, X_t is the is the transition equation at time t. c and d are constants, ε_t is the measurement error and z_t is the state error.

The Kalman filter is an algorithm that provides to estimate of random and uncertain observations bu using a series of observed measurements to filter out noise. It projects the unknown measurements (noises) onto the transition equation. It also assumes that “the state of a system at a time t evolved from the prior state at time t-1, according to the equation” (Faragher, 2012: 128).

The filter is used mostly in the field of information processing. It is also widely accepted in time series analysis used in econometrics.