

Institutional Herding in Borsa İstanbul

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Institutional Herding in Borsa İstanbul

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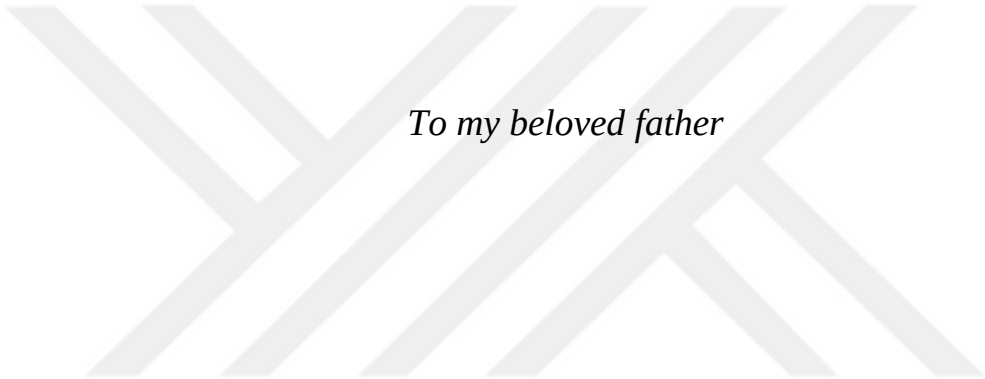
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To my beloved father

ABSTRACT

Herding is defined as a group of investors imitating the actions of other investors instead of following their own beliefs and information. It is argued that institutional investors have several reasons to herd. The theoretical explanations of herding are categorized as informational cascades, reputational and compensational herding, characteristic herding, investigative herding and fads. The herding behaviour of both domestic and foreign institutional investors is analysed in Borsa İstanbul between March 2006 and September 2018 by using the Sias [1]'s herding measure.

The institutional demand for stocks in the current quarter is positively correlated with the institutional demand for stocks in the previous quarter for both domestic and foreign institutional investors. This positive relation is decomposed into institutional investors following their own lag trades and institutional investors following each other into and out of the same securities ("herding") parts. This positive relation is not caused by the characteristics herding and momentum trading strategies. The institutional demand for stocks in the current quarter has no destabilizing effect on future stock returns. The domestic institutional investors herd only in small-capitalization stocks which is interpreted as informational cascades. The foreign institutional investors herd in both small and large-capitalization stocks. The evidence of herding in large capitalization stocks is interpreted as investigative herding. The domestic institutions implement negative feedback trading strategies in large-capitalization stocks while foreign institutional investors implement positive feedback trading strategies in large-capitalization stocks.

ÖZET

Bir grup yatırımcının kendi inançları ve bilgilerini göz ardı ederek diğer yatırımcıların davranışlarını taklit etmesi sürü davranışı olarak tanımlanır. Kurumsal yatırımcıların sürü halinde hareket etmeleri için birçok neden vardır. Bu teorik açıklamaları bilgisel şelaleler, saygınlık ve ücrete dayalı endişelere dayalı, hisse karakterlerine dayalı, araştırmaya ve heveslere dayalı sürü davranışları olarak kategorize edilir. Bu çalışmada Borsa İstanbul'da Mart 2006-Eylül 2018 döneminde kurumsal yerli ve yabancı yatırımcıların sürü davranışı, Sias [1]'ün sürü davranışı ölçüsünü kullanarak analiz edilmiştir.

Yerli ve yabancı kurumsal yatırımcıların hisseye olan bu çeyrekteki talepleri ile geçen çeyrekteki talepleri arasında pozitif korelasyon bulunmaktadır. Bu pozitif korelasyon yatırımcıların kendi geçmiş işlemlerini takip ettiği ve diğer yatırımcıların alım-satımlarını takip ettiği (sürü davranışı) şeklinde iki parçaya ayrılmıştır. Bu pozitif korelasyon kurumsal yatırımcıların aynı özelliklere sahip hisselerle yatırım yapması ya da momentum alım-satım stratejileri uygulamalarından kaynaklanmamaktadır. Kurumsal yatırımcıların bu dönemki taleplerinin, hisse senetlerinin gelecekteki getirileri üzerinde istikrarsızlık yaratıcı etkisi bulunmamaktadır. Yerli kurumsal yatırımcıların düşük piyasa değerine sahip hisselerde sürü davranışı göstermeleri bilgisel şelalelere dayalı sürü davranışı olarak sınıflandırılır. Yabancı kurumsal yatırımcılar hem düşük hem de yüksek piyasa değerine sahip hisselerde sürü davranışına girmektedirler. Yüksek piyasa değerine sahip hisselerdeki sürü davranışı araştırmacı sürü davranışı olarak yorumlanabilir. Yerli kurumsal yatırımcılar yüksek piyasa değerine sahip hisselerde negatif geri bildirim alım-satım stratejileri uygularken, yabancı kurumsal yatırımcılar pozitif geri bildirim alım-satım stratejileri uygulamaktadır.

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CHAPTER I

INTRODUCTION

This Ph.D. dissertation is about herding behavior of both domestic and foreign institutional investors in Borsa İstanbul. It contributes to the herding literature by analyzing both domestic and foreign institutions in an emerging market. Chapter II is a comprehensive literature review of herding in financial markets. Chapter III analyzes herding behavior of domestic institutional investors. Chapter IV examines the herding behavior of foreign institutional investors. Finally, Chapter V concludes by summarizing the main findings of the analysis.

In chapter II, I discuss the various theoretical explanations of herding behavior in financial markets. Then, I introduce the herding measures used in the empirical analyses. The first group of measures uses aggregate market data, and the second group of measures uses the holdings data. Then, I discuss the empirical studies conducted by using these measures. Finally, I summarize the herding studies in Turkish markets.

I investigate the herding behavior of domestic institutional investors in chapter III by using the data obtained from Takasbank. I use the methodology described by Sias [1] to analyze the herding behavior. The cross-sectional correlations between institutional demand in the current quarter and the previous quarter are calculated and these cross-sectional correlations are further decomposed into institutions following their own trades and following others' trades parts. The results indicate that herding behavior exists among domestic institutions but this behavior results from stocks with relatively few traders.

I examine the cross-sectional correlation between the fraction of institutions increasing portfolio weights in the current and previous quarter to determine whether the institutional herding results from habit investing which is a special type of characteristic herding. The results reveal little evidence that herding is driven by cross-sectional and time-series correlation in net flows to institutional investors. I examine momentum trading, returns and herding by market capitalization to test for the reasons of institutional herding. I find evidence of momentum trading but it is not a main factor in explaining the herding behavior. I investigate the relation between the institutional demand in the current quarter and the stock returns in the future periods to identify any destabilizing effect of the herding behavior in the stock returns. The institutional demand hasn't any destabilizing effect in the market. However, there is a negative relation between the current institutional demand and returns in the current period for stocks with at least 20 actively trading institutions. The domestic institutions buy the stocks that are underperforming and sell the stocks that are overperforming. Finally, the analysis of herding by market capitalization reveals that domestic institutional herding is driven by stocks with small market capitalization.

I repeat the same analysis for foreign institutions in Chapter IV. The results reveal that herding behavior is stronger among foreign institutions compared to domestic institutions. The herding behavior is not driven by habit investing. The foreign institutions implement more momentum trading strategies than the domestic institutions. There aren't any destabilizing effects of foreign institutional demand on future stock returns. The analysis of herding by market capitalization indicates that the foreign institutions herd both in small and large capitalization stocks. Finally, the returns of the stocks bought and sold by domestic and foreign institutions are analyzed. The results reveal that the

domestic institutions are negative feedback traders and the foreign institutions are positive feedback traders.



CHAPTER II

LITERATURE REVIEW OF HERDING BEHAVIOR

2.1 Introduction

The preliminary studies on finance are based on the assumption of a rational agent who acts rationally with perfect information and who seeks to maximize wealth in a perfectly competitive market [2]. There is an enormous amount of data available for decision-making in the financial markets. It is assumed that agents in the financial markets process this information and give rational decisions. The Efficient Market Hypothesis of Fama [3] proposes how information is incorporated into security prices. However, the body of work that is called behavioral finance challenges the rational man assumption of the traditional finance. Detailed works on bounded rationality [4], prospect theory [5] and psychological biases [6] on decision-making gained popularity and shed more light on how financial decisions are given. The researchers identify several cognitive biases that can lead to investment mistakes and herding is one of the biases that is widely studied in behavioral finance.

Herding is defined as the behavior of individuals in a group acting collectively without any centralized direction ([7]). Bartels [8] explains the psychology behind herding as individuals believe that a large group of people cannot be wrong and they feel secure by not going against the crowd. The herding term in finance is defined as the process in which financial agents imitate the actions of other financial agents [9]. Nofsinger & Sias [10] define herding in financial markets as “a group of investors trading

in the same direction over a period of time”. Hwang & Salmon [11] argue that “herding arises when investors decide to imitate the observed decisions of others or movements in the market rather than follow their own beliefs and information”. Hirshleifer & Teoh [12] define herding as the “convergence of actions and behaviors of investors” and list possible herding areas in finance as:

- Investors in deciding whether to participate in market
- Investors in deciding which securities to trade and whether to buy or sell
- Analysts and investors in deciding which securities to discuss and study
- Analysts in the forecasts they make
- Firms in their investment, financing and reporting decisions.

Herding in financial markets is a hot topic that draws the attention of researchers. The bibliometric study of Choi *et al.* [13] report an increasing interest in the herding behavior especially after the subprime crisis of 2008. The concerns about the increasing volatility effects, distortion of the market stability and increases in the fragility of the financial markets as a result of herding behavior are the main motivations behind this increase in interest. Choi *et al.* [13] classify the studies on herding into five groups: “i) understanding and contagion, ii) extension and effects, iii) behavior during crises, iv) investment, and v) portfolio management”. Bikhchandani & Sharma [14], Hirshleifer & Teoh [12] and Spyrou [9] provide detailed reviews of both theoretical and empirical studies in the herding literature. While the attention of researchers increases after the 2000’s, the roots of the conceptualization of herding in financial markets can be traced back to the seminal work of Keynes. Keynes [15] claims that professional money managers will participate in the herd if they are concerned about how others will assess their ability to make sound judgements. The history of financial markets is also full of

episodes, where investors create bubbles and crashes in different assets in a herd mentality like lemmings ([16]; [17]; [18]; [19]). Even the father of physics Isaac Newton muttered that he “could calculate the motions of the heavenly bodies, but not the madness of the people” in trading South Sea Company shares. Today the trading activities of most individual investors in meme stocks like AMC and GameStop ([20]) and cryptocurrencies ([21]; [22]) resemble the behavior of the crowds in the past.

The individual investors tend to herd due to uncertainties and insufficient information in making financial decisions. However, Lakonishok, Shleifer & Vishny [23] claim that “herding might be more prevalent among institutions than among individuals.” Institutions monitor the trading activities of other institutions more closely than the individuals. They infer information about the quality of investments from each other’s trades and start a herd. Furthermore, separating luck from skill in evaluating the performance of money managers is a difficult task. Since managers are evaluated against each other, they have an incentive to buy and sell the same assets as other managers do and this may lead to a herding behavior. Lastly, institutions follow the same signals and they may react to changes in these signals in the same way and this can also start a herd behavior.

The purpose of this study is to find whether institutional herding exists in Borsa İstanbul (BİST) and investigate the reasons that cause it and search for evidence of any destabilizing effects of this herding behavior. In this chapter, a detailed literature review on herding behavior in the financial markets is presented, and the detailed analysis of the institutional herding behavior in BİST is explained in the following chapters.

2.2 Theories of Herding Behavior

The studies on herding literature start with theoretical explanations ([24]; [25]; [26]) and then continue with empirical studies ([23]; [27]; [28]). There are several explanations for herding behavior in financial markets which differ in causes and consequences. The formation of herding behavior can be categorized as intentional or unintentional and intentional herding can be classified as rational or irrational. Bikhchandani & Sharma [14] distinguish between “spurious herding” and “intentional herding.” The spurious herding results from agents taking similar decisions when they are facing similar problems and information sets. A group of agents in the financial markets may react to new information that they are all watching, in the same way by selling and buying collectively. This unintentional collective action of agents does not qualify as a real herding behavior and its outcome is considered as efficient. Sias [1] names spurious herding as “investigative herding” and it arises when investors’ information is positively cross-sectionally correlated. Short-term horizons of investors as explained in [29] may cause this type of herding behavior. In their model short-term investors liquidate their positions before any public news arrives. If more investors trade on the same information, the more an investor will make a profit. The investors with short-term horizons focus their research efforts on the same sets of information and trade in the same way as other investors and this creates a herding behavior. Hirshleifer, Subrahmanyam & Titman [30] develop another model of herding behavior driven by information acquisition with different types of investors. In their model, some investors discover information early than others and trade by using that information in the first period and liquidate their positions in the next period. If a greater amount of late-informed investors trade on this information in the next round, the early-informed investors exit from the position more profitably. Thus, investors find gathering information about assets that are followed by

many other investors very attractive. This also leads the investors to follow the same set of information and act collectively as in herd behavior.

Intentional herding occurs when investors mimicked the behavior of other investors by ignoring their own private information. If this intentional behavior depends on information, then it is called as rational herding. If it is not based on information, then it is called irrational herding. Possible reasons for intentional and rational herding are informational cascades, reputational and compensational concerns and the outcome of this herding type may not be an efficient one. Sias [1] argues that herding behavior due to reputational and compensational concerns is non-informational and therefore is not considered as a rational behavior. The unintentional herding can be driven by sentiment, characteristics investing and fads, and they are all irrational types of herding behavior. The irrational herding may result in fragile markets, excess volatility, and systemic risk in the financial system.

2.2.1 Rational Theories of Herding

Devenow & Welch [31] state that rational explanations of herding behavior arise from negative externalities, positive externalities, principal-agent problems and informational learning (cascades).

An example of the negative payoff externalities is the bank runs created by the panic of the depositors. Diamond & Dybvig [32] illustrate one of the rational theories for herding behavior. If there is a bank run, the depositors rush to withdraw their deposits because of the risk of bank failure. In this bank run model, the depositors of the bank should join the queue of waiting depositors in front of the bank because the bank will meet withdrawal requests on a first come first served basis and it may not be able to meet

all withdrawal requests. Thus, joining the herd is a rational choice for depositors in this model.

Liquidity can be regarded as a positive externality since investors prefer liquid markets and increased liquidity in a market can encourage investors to cluster in that market and this may result in concentrated trading ([33]; [34]).

Scharfstein & Stein [24] discuss the motives of investment managers' tendency to follow the herd as a rational behavior in a reputational concern context. In their model there are two types of managers. Smart managers receive informative signals about the value of an investment, and worse managers receive noisy signals. Initially, neither the managers themselves nor the labor market can identify the types. However, after the managers made an investment decision, the market can update its beliefs based on whether the manager's investment decision is profitable or the manager's behavior is similar or different from the investment decisions of the other managers. Unpredictable shocks will lead to unwanted investment results and smart investors may have bad periods in terms of profitability. However, the managers will not be evaluated unfavorably if they follow the decisions of the other managers. Sharing the blame effect will keep their reputations intact. On the other hand, being a contrarian in the market can have adverse reputational effects and the labor market can label the contrarians as worse types. Scharfstein & Stein [24] conclude that mimicking the behavior of others and ignoring private information can be rational due to reputation concerns in the labor market. Then, they give real-world examples of the theoretical model in bank lending to emerging markets, portfolio managers in the stock market and decision-making within firms.

Zwiebel [35] develops a model of reputational herding of managers based on relative performance and absolute action instead of Scharfstein & Stein [24]'s model of

absolute performance and relative action. In this model, managers choose between a project based on existing technology and a project that uses a new innovative technology. The project with the new technology has a higher expected return but gives less accurate information about the performance of the manager. The model shows that both low and highly-skilled managers choose the new technology but medium-skilled managers prefer to invest in the old technology. The medium-skilled managers' herding towards the old technology results from their concerns of misevaluation in the labor market, which outweighs the higher expected returns of the new technology.

Rajan [36] constructs a model of bank management with short-term earnings and the labor market's perception of its abilities (reputation) concerns. The bank management has incentives to relax their credit standards to increase short-term earnings and does not set aside any loan-loss reserves. The bank management's reputation remains intact when even the high-ability managers perform poorly due to the bad state of the world. He also shows a model of two banks herding in loans to the same sectors is the optimal action for them.

Analysts in financial markets have an important role because of their recommendations and forecasts. Their analyses are used by their own institutions and investors who follow them. The literature delves into analysts' herding in recommendations. Trueman [37] develops a model in which an analyst releases a forecast similar to the forecasts previously made by other analysts to favorably affect the investors' evaluation of the analyst's forecasting ability. Graham [38] develops a model in which an analyst will herd if he has a "high reputation, low ability, or if there is strong public information that is inconsistent with the analyst's private information." Avery & Chevalier [39]; Chevalier *et al.* [40]; Hong *et al.* [41]; and Lamont [42] discuss the

relation between reputation and herding where managers opt to herd in their early career by ignoring their own abilities.

Investment managers may have compensation concerns besides reputation concerns and this concern may also lead to a herding behavior. An investment manager's compensation depends on his or her relative performance compared to the other investors, or a benchmark. Maug & Naik [43] argue that a risk-averse investor whose compensation is linked to his relative performance compared to a benchmark may have an incentive to mimic the benchmark's composition to decrease the risk of losing a part of his income. This may create herding towards benchmark among market participants.

Information is important in making decisions but it is not homogeneously distributed as explained in the seminal work of Akerlof [44]. Furthermore, the investors may have limited access to information or they may have to pay a high cost to acquire information. In this case, investors may ignore their own private information and follow the others' decisions and this may create a herding behavior due to informational cascades.

Banerjee [25] and Bikhchandani *et al.* [45] demonstrate a simple model of herd behavior in a dynamic sequential decision-making game. Each decision-maker looks at the decisions made by previous decision-makers because previous decision-makers may have superior information. After seeing the decision of the previous player, the next decision-maker will give the same decision by ignoring his or her own private information and this will start a herd behavior in the market.

Bikhchandani & Sharma [14] model the formation of herding driven by informational cascades. In their model there are several foreign direct investors deciding sequentially to invest in an emerging market country that is implementing a fixed

exchange rate regime. θ denotes the payoff to invest in that country relative to investment in the next best country. The payoff from the best next investment is normalized to zero, and θ can be either +1 or -1 with equal probability. The order in which the investors decide to invest is determined exogenously. Each investor observes a private signal about the payoff of the investment. This signal can be high (H) or low (L). If $\theta = +1$, then the probability that the signal is H equals to p , while the signal L has a probability of $1-p$, where p lies between 0.5 and 1. If $\theta = -1$, then the probability that the signal is L is equal to p , while the signal H has a probability of $1-p$. The signals are independent conditional on the true value of the investment but the investors do not have any information about the private signals that other investors received. However, they observe the decisions made by the predecessors. Using Bayes' rule, Bikhchandani & Sharma [14] state that the posterior probability of $\theta = +1$ after observing signal H is:

$$\begin{aligned}
 & P[\theta = +1|H] \\
 &= \frac{(P[H|\theta = +1] \times P[\theta = +1])}{(P[H|\theta = +1] \times P[\theta = +1]) + (P[H|\theta = -1] \times P[\theta = -1])} \quad (1) \\
 &= \frac{p \times 0.5}{p \times 0.5 + (1 - p) \times 0.5} = p > 0.5
 \end{aligned}$$

The posterior probability of $\theta = +1$ after receiving signal L is:

$$\begin{aligned}
 & P[\theta = +1|L] \\
 &= \frac{(P[L|\theta = +1] \times P[\theta = +1])}{(P[L|\theta = +1] \times P[\theta = +1]) + (P[L|\theta = -1] \times P[\theta = -1])} \quad (2) \\
 &= \frac{(1 - p) \times 0.5}{p \times 0.5 + (1 - p) \times 0.5} = 1 - p < 0.5
 \end{aligned}$$

The first investor X will follow his signal and he will invest if he receives signal H, and will not invest if he receives signal L. The second investor Y observes the decision of investor X and infers the signal that investor X receives by observing X's decision. If the second investor's signal is H (L) and sees that the first investor invests (rejects), then he will also invest (reject to invest) in the country. However, if the second investor's signal is L and he observes the first investor invests, investor Y will be indifferent between investing or rejecting (because the posterior probability $\theta = +1$ is equal to 0.5) and will decide by flipping a coin.

$$\begin{aligned}
 & P[\theta = +1|H, L] \\
 &= \frac{(P[H|\theta = +1] \times P[L|\theta = +1] \times P[\theta = +1])}{(P[H|\theta = +1] \times P[L|\theta = +1] \times P[\theta = +1]) + (P[H|\theta = +1] \times P[L|\theta = -1] \times P[\theta = -1])} \quad (3) \\
 &= \frac{0.5p(1-p)}{0.5p(1-p) + 0.5(1-p)p} = 0.5
 \end{aligned}$$

If investor X invests and investor Y rejects, then the third investor Z will infer that the first investor's signal was H, and the second investor's signal was L. If both first two investors invest, then the third investor Z will infer that the first investor's signal is H and the second investor's signal is more likely H rather than L. If investor X rejects and investor Y invests, then the third investor Z will infer that the first investor's signal was L, and the second investor's signal was H. If both first two investors reject, then the third investor Z will infer that the first investor's signal is L and the second investor's signal is more likely L rather than H.

When both investors X and Y invest, at this point cascade starts. Then, investor Z infers that the predecessors received signal H. By applying another Bayes' rule, it can be

shown that investor Z should always invest regardless of his own private signal. Even if the third investor receives signal L, his posterior probability that $\theta = +1$ is more than 0.5 because investor Z's L signal and investor X's H signal cancel each other and after observing investor Y's action, investor Z thinks that the second investor's signal is H rather than L. At his point, the third investor is in an invest cascade and the following investors will also herd in investing to the country regardless of their own private signals. If the first two investors reject to invest, then the third investor will also reject without considering his own private signal. This is defined as a reject cascade. If the first two investors take opposite actions, then the third investor infers that one of them saw the good signal and the other one saw the bad signal. His prior beliefs about the value of the investment ($\theta = +1$ and $\theta = -1$) are equally likely, and he will proceed according to his own signal. Bikhchandani & Sharma [14] propose that an investor will be in an "invest cascade" ("reject cascade") if and only if the number of predecessors who invest is greater (less) than the number of predecessors who reject by two or more. The summary of the process is shown in Figure 1. The figure shows the formation of herding driven by informational cascades in a model with several foreign direct investors deciding sequentially to invest in an emerging market country that is implementing fixed exchange rate regime.

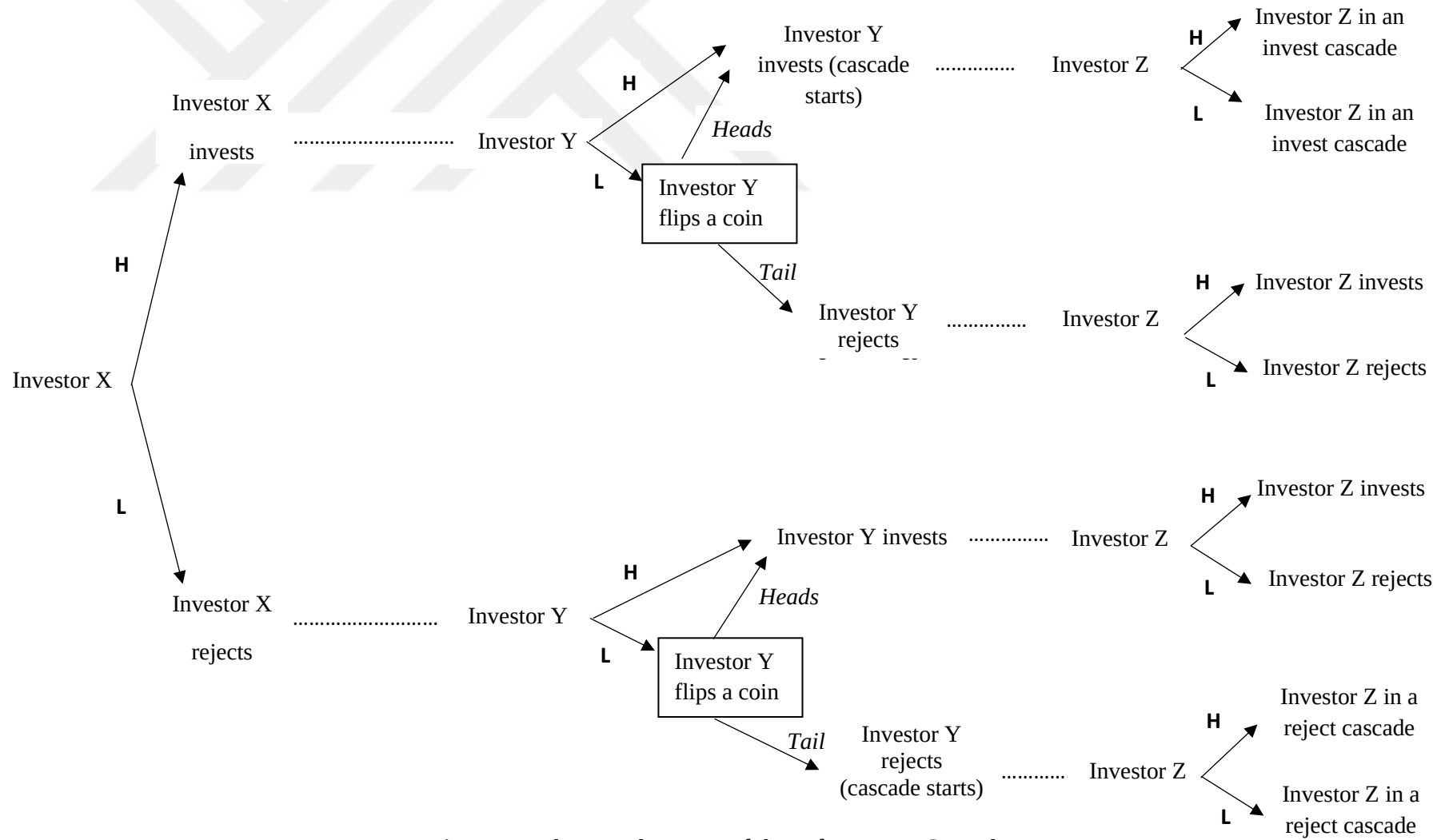


Figure 1: The Development of the Information Cascades

Bikhchandani & Sharma [14] assume that the price is fixed and does not change due to invest or do not invest decisions of the investors. However, stock prices adjust as investors make buy and sell decisions. If the prices adjust to reflect the expected value of the investment conditional on all the publicly available information, then cascades never start. Bikhchandani & Sharma [14] modify the model to take into account the flexible prices. The initial price of the investment is set to be zero, the true value of investment θ is again either + 1 or -1 with equal probability and investors receive a private signal that is correct with probability p ($0.5 < p < 1$). If the first investor X receives signal H and buys, then the stock price will increase to $2p-1$ which is the expected value of the stock conditional on investor X's H signal. If investor Y receives L signal, the posterior expected value of the stock will be zero and will not invest because $0 < 2p-1$. If the investor Y receives H signal and observes investor X invest, then the posterior expected value of the stock is $[(2p-1)/(p^2+(1-p)^2)]$ and it is greater than the price of the stock $2p-1$. If investor X does not invest, the price that investor Y faces will be $1-2p$. If investor Y receives H signal, the posterior expected value of the stock will be zero and will invest because $0 > 1-2p$. If investor Y receives L signal, the posterior expected value of the stock will be $[(1-2p)/(p^2+(1-p)^2)]$ and it is less than the price of the stock $1-2p$. Thus, investor Y follows his private signal, whatever the first investor decides and information cascades never starts.

Avery & Zemsky [46] add another uncertainty to the model to solve the flexible price problem. In their model, there are two types of investors, S and U. Type S investors are more skilled and have more accurate information (p_s close to 1) and type U investors are less skilled and have noisier information (p_u close to 0.5). Furthermore, the proportion of the two types of investors in the population is not known. The price reflects all publicly

available information and choices of the predecessor investors, but it does not give information about the types of the investors. Information cascades can emerge when most investors are type S and they have the same private signal. If most of the predecessor investors are type U, but the decision-makers believe that they are mostly type S, then an inefficient cascade may arise. The following investors may imitate the predecessor investors by believing erroneously that the predecessors have significant private information.

Welch [26] develops a cascade model of herding in an IPO setting. If the distribution channels of the investment banks are limited, then potential investors will be contacted sequentially. If the first approached investors are eager to participate in the IPO, the later approached investors will observe these successful initial sales efforts and interpret that demand as a sign of favorable information. If the initial demand from the first approached investors is weak, then later approached investors will be reluctant to participate in the IPO ignoring their private information and this leads to cascades.

Doherty [47] provides an extensive review of theoretical explanations of information cascades. Anderson & Holt ([48], [49]) provide evidence for the formation of information cascades in laboratory experiments. The question of whether the outcome of informational cascades is efficient or not is also important. There is a group of investors that are reviewing plans to invest in an emerging market and the majority of them have negative views while remaining minority has positive views. If the investors pool their information, the collective decision will be to skip that investment. If the first decision-makers are the investors that have optimistic view, then the remaining pessimistic investors may disregard their own beliefs and participate in an invest cascade. If the investment turns out to be unprofitable then the investors will close their positions by selling and this will create a herd in the opposite direction. The outcome of the

information cascade is inefficient and the massive inflows and outflows from the emerging market will also increase the volatility in stock returns and the currency.

2.2.2 Irrational Theories of Herding

The irrational herding behavior is not based on information and it is driven by sentiment, characteristics investing and fads. This type of herding bears the risk of creating excess volatility, bubbles and crashes in the markets.

The sentiment of investors is a key factor in making decisions and sentiment changes a lot. The psychology of the investors drives the sentiment and the sentiment moves in cycles. The feeling of fear and uncertainty dominate one extreme of the sentiment and greed and hubris dominate the other extreme. We are always hearing commentaries on financial networks that investors are buying assets due to fear-of-missing-out (FOMO) and selling assets due to fear, uncertainty and doubt (FUD) in risk-off episodes. These shifts in the sentiment lead to collective buying and selling of investors in different asset classes. The investors flock into US Treasuries by selling stocks when fear dominates and sell US Treasuries to buy back stocks when fear disappears. The sentiment also determines the flows to FAANG stocks (Facebook, Amazon, Apple, Netflix and Google). The investors buy and sell these stocks collectively due to changes in their sentiment and this collective action of investors is a type of herding behavior.

Fads and hype also play an important role in investors' decision-making. Shiller [50] argues that investors discuss, read and gossip about their investments. These social interactions and extensive media coverage can popularize a specific asset class, sector or stock among investors. The term of meme stocks is used for stocks that have high popularity due to social media discussions and significant retail investor trading,

commonly resulting in inflated prices. The increased attention of investors due to fads and hype may lead to a herding behavior as increased collective buying activity during the popularization phase of the asset class, sector, or stock and collective selling activity after the popularization is exhausted. The investment decisions given by fads and hype may create a divergence from the fundamental value of the asset. An investor will buy the asset at a price higher than its fundamental value if that investor expects to sell it at a higher price later and this process may lead to a speculative bubble and crash.

The investors' attraction to securities with specific characteristics is a well-documented fact in the financial markets. Falkenstein [51] argues that mutual funds prefer to hold stocks with high volatility, large size, and high liquidity. Small firm stocks and stocks with little information are avoided in the portfolios of mutual funds. Gompers & Metrick [52] find that institutions prefer stocks that are large in size, have high liquidity, and have low returns in the previous year. Badrinath *et al.* [53] identify that insurance portfolio managers prefer stocks larger in size, with high liquidity, high age, high stock ranking, and high previous performance. Bennett, Sias & Starks [54] claim that institutional investors' preferences have shifted from large-capitalization stocks to smaller and riskier stocks. These findings indicate that institutional investors prefer to hold stocks with certain characteristics in their portfolios. There are also many funds that are specialized in style investing. These funds only invest in stocks with certain characteristics. The growth of style investing funds and the tendency of institutional investors to hold stocks with specific characteristics in their portfolios may lead to an emergence of herding behavior. These funds buy and sell the stocks with same characteristics and this buy and sell activity is classified as herding driven by characteristics.

Positive feedback investment strategies which are widely used by investors in the markets are a special case of herding. Positive feedback strategies involve buying assets appreciated and selling assets depreciated in value (buying past winners & selling past losers). These strategies are also named as momentum trading and are documented by Jegadeesh and Titman [55]. Momentum is also considered as a stock characteristic that is preferred by investors. If a significant number of investors buy the past winner stocks and sell the past loser stocks, then this may result in a herding behavior in the market. Herding due to positive feedback strategies and whether it creates a stabilizing or destabilizing effect on stock prices are widely investigated in the academic literature. De Long *et al.* [56] construct a model in which positive feedback trading strategies of rational speculators can have destabilizing effects on stock prices. Shleifer [57] argues that positive feedback trading strategies may have destabilizing price effects in the markets and may create bubbles in the market.

The extant literature on herding lists many reasons for herding behavior, but highlighting a single reason as the primary cause of herding is not possible in academic studies. This variety of theoretical explanations leads to difficulties in the identification and measurement of herding behavior in empirical studies.

2.3 Measures of Herding

There are different causes of herding behavior with different consequences and it is not an easy task to differentiate empirically between different types of herding, especially between the spurious and intentional herding. Spyrou [9] classifies empirical methodologies of herd behavior into two main categories. The first category is the studies that rely on aggregate price and market activity data and investigate herding towards the

market consensus. The second category investigates whether specific investor types herd by using proprietary data of changes in investors' holdings.

2.3.1 Herding Measures Using Aggregate Market Data

The herding measures that use macro-level market data investigate whether herding exists at the aggregate market level. Christie & Huang [27] first propose a measure based on the herding towards the market consensus. They claim that investors will probably ignore their own beliefs during market stress and follow the market wide consensus.

The rational asset pricing models predict that market return changes will be large during volatile time periods and individual stock returns will have high dispersions (high cross-sectional standard deviations). The proponents of herding behavior claim that investors are more likely to ignore their own beliefs during market stress and dispersion will be low in these times and low dispersion can be used as an evidence of herd behavior. The cross-sectional standard deviation (CSSD) at time t is defined to measure the dispersion as:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^N (R_{i,t} - R_{m,t})^2}{N - 1}} \quad (4)$$

where $R_{i,t}$ is the observed return on stock i at time t and $R_{m,t}$ is the cross-sectional average return of the N stocks at time t . This metric of herding behavior measures the dispersion of asset returns around the realized average market return. If the level of dispersion is high in volatile market conditions, then investors are said to be acting rationally but if the dispersion is low, then herding behavior exists in the market. To differentiate between these two hypotheses, the level of dispersion, $CSSD_t$ is analyzed

only for the extreme tails of the distribution of market returns and compared with average levels of dispersion that exclude the market returns in the extreme tails. The dispersion level in market stress periods is tested by using the following linear regression model:

$$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t \quad (5)$$

where,

$D_t^L = 1$ if the market return on time period t is in the extreme lower tail of the return distribution,

$D_t^L = 0$ otherwise,

and

$D_t^U = 1$ if the market return on time period t is in the extreme upper tail of the return distribution,

$D_t^U = 0$ otherwise.

The coefficient α denotes the average dispersion of the sample excluding extreme tails. Positive coefficients for β^L and β^U mean that investors follow their own beliefs and it is considered as an evidence of rational investor behavior in the market. Negative estimates of β^L and β^U are considered as the presence of herding behavior in the market under stressful conditions because negative coefficients mean that investors ignore their own beliefs and herd towards market consensus.

Chang *et al.* [58] develop an alternative herding measure based on the idea of Christie & Huang [27]'s average dispersion of individual stock returns from the market return. It is argued that rational asset pricing models predict the return dispersions of

stocks as an increasing function of the market return and their relation is also linear. If investors tend to follow the aggregate market behavior by ignoring their own beliefs during periods of large changes in the prices, then the assumed linear and increasing relation between dispersion and market return will no longer exist. The relation will become non-linearly increasing or decreasing. The evidence of non-linearly increasing or even decreasing relation is considered as an evidence of herding in the market.

The model starts with the conditional version of the Black [59]'s CAPM:

$$E_t(R_i) = \gamma_0 + \beta_i E_t(R_m - \gamma_0) \quad (6)$$

where $E_t(.)$ denotes the expectation in period t , R_i denotes the return of stock i , R_m is the return of the market, γ_0 is the return of the risk-free rate, β_i is the systematic risk measure of the stock, $i = 1; \dots; N$ and $t = 1; \dots; T$. And, β_m denotes the systematic risk of an equally-weighted market portfolio:

$$\beta_m = \frac{1}{N} \sum_{i=1}^N \beta_i \quad (7)$$

The absolute value of the deviation (AVD) of stock i 's expected return from the portfolio's expected return in time period t is expressed as:(8)

$$AVD_{i,t} = |\beta_i - \beta_m| E_t(R_m - \gamma_0) \quad (8)$$

The expected cross-sectional absolute deviation of stock returns (ECSAD) in time period t is defined as:

$$ECSAD_t = \frac{1}{N} \sum_{i=1}^N AVD_{i,t} = \frac{1}{N} \sum_{i=1}^N |\beta_i - \beta_m| E_t(R_m - \gamma_0) \quad (9)$$

The linear and increasing relation between dispersion and the market's expected returns is demonstrated as:

$$\frac{\partial ECSAD_t}{\partial E_t(R_m)} = \frac{1}{N} \sum_{i=1}^N |\beta_i - \beta_m| > 0 \quad (10)$$

$$\frac{\partial^2 ECSAD_t}{\partial E_t(R_m)^2} = 0 \quad (11)$$

Since $ECSAD_t$ and $E_t(R_{m,t})$ are unobservable, the realized cross-sectional absolute deviation of returns (CSAD) and realized $R_{m,t}$ at time t are used as proxies:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^N |R_{i,t} - R_{m,t}| \quad (12)$$

where CSAD is estimated as the average absolute value of each stock's return deviation (AVD) from the return of the equally weighted market portfolio. $R_{i,t}$ is the return of stock i in period t, $R_{m,t}$ is the cross-sectional average return of the market portfolio in time t, and N is the total number of stocks. CSAD is not a stand-alone herding measure. However, the relationship between $CSAD_t$ and $R_{m,t}$ is used together for identifying the herding behavior. If herding is present during periods of extreme market conditions, then there should be a smaller increase or even a decrease in the CSAD measure.

The following regressions are estimated to check for the possibility of asymmetry in the up and down markets' herding:

$$CSAD_t^{UP} = \alpha + \gamma_1^{UP} |R_{m,t}^{UP}| + \gamma_2^{UP} (R_{m,t}^{UP})^2 + \varepsilon_t \quad (13)$$

$$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN} |R_{m,t}^{DOWN}| + \gamma_2^{DOWN} (R_{m,t}^{DOWN})^2 + \varepsilon_t \quad (14)$$

where $CSAD_t$ is the average AVD_t of each stock relative to the return of the equally-weighted market portfolio, $R_{m,t}$ in time period t . $|R_{m,t}^{UP}|$ is the absolute value of an equally-weighted realized return of all the stocks at time t when the market is up. $|R_{m,t}^{DOWN}|$ is the absolute value of an equally-weighted realized return of all the stocks at time t when the market is down. If investors tend to herd towards the market under stressful market conditions, there will be a negative non-linear relation between CSAD and the average market return and it is captured by the γ_2 term. A positive γ_2 coefficient is interpreted as an evidence for rational asset pricing, and there is no evidence of herding in the market.

Hwang & Salmon [11] formulates a new way of measuring herding based on studying the deviations from the equilibrium beliefs reflected in CAPM prices. In their model, herding behavior leads to mispricing of individual assets because of biased betas due to the suppression of equilibrium beliefs. Their idea is similar to Christie & Huang's model but they use cross-sectional dispersion of the betas instead of returns. The model starts with the CAPM model of Sharpe [60], and Lintner [61]:

$$E_t(r_{it}) = \beta_{imt} E_t(r_{mt}) \quad (15)$$

where r_{it} and r_{mt} are the excess returns on stock i and the market at time t , β_{imt} is the systematic risk measure, and $E_t(\cdot)$ is a conditional expectation at time t .

It is assumed that $E_t(r_{mt})$ is set by the market-wide consensus and the investors first construct a view of the market and then value the individual asset. In the case of herding towards the market, the investors ignore the equilibrium relationship β_{imt} and match the return on individual assets with the return of the market. This view is expressed in the model by the following relationship:

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1) \quad (16)$$

where $E_t^b(r_{it})$ and β_{imt}^b are the market's biased conditional expectation on the excess returns of stock i and the stock's beta at time t , and h_{mt} is a latent herding parameter that is changing with time.

When $h_{mt} = 0$, then β_{imt}^b will be equal to β_{imt} , then there is no herding behavior in the market and CAPM holds. When $h_{mt} = 1$, then $\beta_{imt}^b = 1$ which is the beta on the market portfolio and the expected excess return of a stock will be equal to the expected excess return of the market portfolio. In this case, there is a perfect herding towards the market portfolio and all the individual stocks will move in the same direction and magnitude as the market portfolio. There is some degree of herding towards the market, when $0 < h_{mt} < 1$.

If the stock's $\beta_{imt} > 1$ (meaning $E_t(r_{it}) > E_t(r_{mt})$), then the equity will herd towards the market by $E_t^b(r_{it})$ approaching to $E_t(r_{mt})$ and $E_t(r_{it}) > E_t^b(r_{it})$. Since $\beta_{imt}^b < \beta_{imt}$, the stock will look less risky and when the market increases (decreases) drastically, the investors will sell (buy) this overperforming (underperforming) stock because it looks like relatively expensive (cheap).

If the stock's $\beta_{imt} < 1$ (meaning $E_t(r_{it}) < E_t(r_{mt})$), the equity will herd towards the market by $E_t^b(r_{it})$ approaching to $E_t(r_{mt})$ and $E_t(r_{it}) < E_t^b(r_{it})$. Since $\beta_{imt}^b > \beta_{imt}$, the stock will look riskier and when the market increases (decreases) drastically, the investors will buy (sell) this underperforming (overperforming) stock because it looks like relatively cheap (expensive).

Due to the fact that, the cross-sectional mean of β_{imt}^b always equals to 1, then:

$$\begin{aligned}
Std_c(\beta_{imt}^b) &= \sqrt{E_c((\beta_{imt} - h_{mt}(\beta_{imt} - 1) - 1)^2)} \\
&= \sqrt{E_c((\beta_{imt} - 1)^2)} (1 - h_{mt}) \\
&= Std_c(\beta_{imt}) (1 - h_{mt})
\end{aligned} \tag{17}$$

where $E_c(\cdot)$ and $Std_c(\cdot)$ are the cross-sectional expectation and the standard deviation. The first item gives the cross-sectional standard deviation of the equilibrium betas and the second item is a direct function of the herding parameter.

To extract h_{mt} from $Std_c(\beta_{imt}^b)$, the logarithms of (17) is taken:

$$\log[Std_c(\beta_{imt}^b)] = \log[Std_c(\beta_{imt})] + \log(1 - h_{mt}) \tag{18}$$

Since the market-wide $Std_c(\beta_{imt})$ is not anticipated to change in the short-run, the changes in $Std_c(\beta_{imt}^b)$ can be attributed to changes in h_{mt} . Based on this expectation, it is written:

$$\log[Std_c(\beta_{imt}^b)] = \mu_m + v_{mt} \tag{19}$$

where $\mu_m = E[\log[Std_c(\beta_{imt})]]$ and $v_{mt} \sim iid(0, \sigma_{mv}^2)$, and then,

$$\log[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + v_{mt} \tag{20}$$

where $H_{mt} = \log(1 - h_{mt})$. This model allows herding term H_{mt} , to change over time as a dynamic process. If it is assumed that H_{mt} follows an AR(1) process, then:

$$H_{mt} = \varphi H_{mt-1} + \eta_{mt} \quad (21)$$

where $\eta_{mt} \sim iid(0, \sigma_{m\eta}^2)$. Hwang & Salmon [11] call this methodology as “the standard state-space model that can be estimated by using Kalman filter approach.” The dynamic pattern of changes in the latent state variable H_{mt} is used to measure herding behavior. When $\sigma_{m\eta}^2 = 0$, $H_{mt} = 0$, then there is no herding behavior. A high value of $\sigma_{m\eta}^2$ indicates that herding exists in the market.

The studies that use aggregate market data for detecting herding are very common because of data availability. However, the assumption that herding metric will converge to market consensus in stressful market times is a very strong one and these metrics do not allow to study herding behavior of subgroups of investors like institutions.

2.3.2 Herding Measures Using Holdings Data

Lakonishok *et al.* [23] argue that there is a corresponding seller for each buyer for every stock at the aggregate level. However, if the researcher focuses on a subgroup of investors, then he may detect an imbalance between the buy and sell decisions of that subgroup of investors. Based on this idea a herding measure is constructed originating from the changes in individual stock holdings of funds and this measure is widely used in herding studies. The herding measure for stock i in time t is formulated as:

$$H_{i,t} = |p_{i,t} - \bar{p}_t| - AF_{i,t} \quad (22)$$

$$p_{i,t} = \frac{B_{i,t}}{B_{i,t} + S_{i,t}} \quad (23)$$

where $B_{i,t}$ is the number of institutional investors that are increasing their holdings of stock i in time t (net buyers), $S_{i,t}$ is the number of institutional investors that are

decreasing their holdings of stock i in time t (net sellers), $\bar{p}_t$ is the average of overall stocks that are traded by at least one of the portfolio managers. $AF_{i,t}$ is an adjustment factor:

$$AF_{i,t} = E[|p_{i,t} - \bar{p}_t|] \quad (24)$$

where the expectation is calculated under the null hypothesis that $B_{i,t}$ has a binomial distribution with parameter $\bar{p}_t$. Under the null hypothesis of no herding, the probability of a randomly chosen institutional investor is a net buyer of stock i is $\bar{p}_t$ and, the expected value of $|p_{i,t} - \bar{p}_t|$ is equal to $AF_{i,t}$. If the number of active traders is large, then $AF_{i,t}$ will approach to zero because $p_{i,t}$ converges to $\bar{p}_t$. The adjustment factor is included in the herding measure to take care of the bias in $|p_{i,t} - \bar{p}_t|$ for stocks in each time period that are not traded by a large number of participants. For a small number of active traders, $AF_{i,t}$ will be generally positive. The herding measure is calculated for each stock in each time period and values of $H_{i,t}$ significantly different from zero are interpreted as an evidence of herd behavior.

Lakonishok *et al.* [23] measure does not indicate the direction of the herding (whether it is a buy herding or sell herding). To overcome this, Wermers [62] develops two separate herding measures for stock i in period t conditional on buy and sell:

$$H_{i,t}^{buy} = H_{i,t} | p_{i,t} - \bar{p}_t > 0 \quad (25)$$

$$H_{i,t}^{sell} = H_{i,t} | p_{i,t} - \bar{p}_t < 0 \quad (26)$$

Grinblatt *et al.* [63] formulate “a signed herding measure (SH) to take into account whether a fund trades with or against the herd”:

$$SH_{i,t} = I_{i,t} \times H_{i,t} - E[I_{i,t} \times H_{i,t}] \quad (27)$$

where $I_{i,t}$ is an indicator function that takes the value of:

- 1 if the fund trades stock i with the herd in period t,
- -1 if the fund trades stock i against the herd in period t, and
- 0 otherwise.

$E[I_{i,t} \times H_{i,t}]$ term considers the possibility that the fund may follow the herd or go against the herd by chance factor. Then, an individual fund herding (FH) measure is developed as:

$$FH = \frac{1}{T} \sum_{t=1}^T \sum_{k=1}^K (w_{i,t} - w_{i,t-1}) \times SH_{i,t} \quad (28)$$

where T represents is the total number of periods in which the fund data is active, K is the total number of stocks held by the individual fund, and $w_{i,t}$ is the weight of stock i in the fund's portfolio in period t.

Lakonishok *et al.* [23] herding measure is criticized for its drawbacks. Bikhchandani & Sharma [64] argue that it uses the number of buyers and sellers for the stock without considering the amount of the buy and sell activity. Wylie [65] questions the accuracy of the measure due to the implicit assumption that portfolio managers may short-sell all the stocks. Bellando [66], Frey *et al.* [67], and Jurkatis [68] argue that LSV measure is a biased estimator and they demonstrate that it underestimates herding behavior by using Monte Carlo simulations.

Lakonishok *et al.* [23] measure is a static herding measure that relies on the contemporaneous trading activities of institutional investors within a specific time period. Sias [1] formulates a dynamic herding measure by using institutional stock holdings data. The formulation starts with the raw fraction of investors buying stock k at time t as:

$$Raw\Delta_{k,t} = \frac{BI_{k,t}}{BI_{k,t} + SI_{k,t}} \quad (29)$$

where $BI_{k,t}$ is the number of institutions that increase their holdings for stock k in period t and $SI_{k,t}$ is the number of institutions that decrease their holdings for stock k in period t . The total of these two numbers gives the number of actively trading investors for that stock in that time period. Then $Raw\Delta_{k,t}$ is standardized to have zero mean and unit variance as follows:

$$\Delta_{k,t} = \frac{Raw\Delta_{k,t} - \overline{Raw\Delta_t}}{\sigma(Raw\Delta_{k,t})} \quad (30)$$

where $\overline{Raw\Delta_t}$ is the cross-sectional average raw fraction of institutions buying in time period t and $\sigma(Raw\Delta_{k,t})$ is the cross-sectional standard deviation of the raw fraction of institutions buying in time period t .

Then, Sias [1] estimates regression of the standardized fraction of institutional buyers of stock k ($\Delta_{k,t}$) in the current period on the standardized fraction of institutional buyers of stock k in the previous period ($\Delta_{k,t-1}$):

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t} \quad (31)$$

The coefficient of β_t is further decomposed into institutions following themselves and institutions following others parts and the institutions following others part is considered as the measure of herding. However, Sias [1] measure also does not consider the buy and sell volume of the investors and assumes short selling is available in the market.

2.4 Empirical Studies

Empirical studies on herding started with Kraus & Stoll [69] for US stocks by using the concept of “parallel trading”. Parallel trading is defined as “a situation in which the trading of a group of investors in a given security at a given time is predominantly on one side of the market”. Weak evidence of herding is found by using the monthly changes in holdings of institutional investors for the period of January 1968 to September 1969. Also, a positive relationship between parallel trading and stock price changes is identified in the current month. Shiller & Pound [70] use survey methodology to provide evidence that institutional investors rely on the advice of other institutional investors in their buy and sell decisions in volatile stocks. The empirical studies increased with the development of herding measures mentioned above. The review of empirical studies is divided into three parts: First, empirical studies that use measures of aggregate market data for herding are presented. Then, the results of studies that use measures of institutional investors’ holdings are discussed. Lastly, herding studies on Turkish markets are presented.

2.4.1 Empirical Studies Using Aggregate Market Data Measures

Christie & Huang ([27], hereinafter CH) test the herding tendency in US equities on a daily basis between 1962 and 1988 and on a monthly basis between 1925 and 1988. By using the regression formulated in Equation (5), the cross-sectional standard deviation of

equity returns is estimated daily and monthly for the stressful market conditions but no evidence of herding behavior is detected.

Chang, Cheng & Khorana ([58], hereinafter CCK) use the regression shown in Equations (13) and (14) to examine herding behavior in the US (1963-1967), Japan (1976-1995), Hong Kong (1981-1995), South Korea (1978-1995) and Taiwan (1976-1995) equity markets. The results indicate that equity return dispersions during the periods of extreme market conditions continue to increase in US, Japan, and Hong Kong markets and this leads to evidence of no herding in these markets. However, the authors find a significant non-linear relationship between equity return dispersion and absolute market return in South Korean and Taiwanese equity markets. The evidence of herding in two emerging market countries can be related to informational asymmetries which are widely accepted to exist more in emerging financial markets. The herding behavior in these two markets does not differ for small or large-capitalization stocks.

The following researchers apply these two methodologies to different asset classes and countries to test for market-wide herding behavior. Gleason *et al.* [71] investigate herding for several commodity futures contracts in European markets. By applying CH [27] measure, the authors reach to the conclusion that herding behavior is not present in futures markets. Gleason *et al.* [72] investigate herding by using CH [27] and CCK [58] measures for US Exchange Traded Funds (ETFs) between 1999 and 2002 by using intra-day data but again fail to find any evidence of herding. Caparrelli *et al.* [73] examine herding in Italian stocks for the sample period of September 1988 to January 2001. The authors first use CH [27] measure and cannot find evidence in favor of the herding hypothesis. Then, they use CCK [58] measure and find evidence of herding for both up and down markets. The evidence of herding is also present in large and small-capitalization stocks.

Goodfellow *et al.* [74] is the first study that analyze herding behavior for individuals and institutional investors separately. There are two quotation systems operated parallel in Polish stock market. One is single-price auction system dominated by individual investors, and the other one is a continuous trading system for large and liquid stocks dominated by institutional investors. The authors test for market-wide herding of these two investor types on a daily basis by using CCK [58] methodology between 1996 and 2000. The results indicate that herding towards the market is present for stocks traded by individuals only. The tendency of herding among individual investors is larger in downward markets compared to upward markets. When the market rises due to positive news, then investors become more confident and rely more on their own information and beliefs. However, when the market starts falling due to bad news, investors lose confidence and this leads them to follow the crowd and asymmetric behavior in falling and rising markets is caused by this reason.

Caporale *et al.* [75] test for the presence of herding in extreme market conditions for the Athens Stock Exchange for the years 1998-2007. They first test the data by using CH [27] measure and fail to find evidence of herding behavior. Then they use CCK [58] measure on daily, weekly and monthly frequencies and find evidence of herding behavior. The herding behavior is stronger in daily frequency and during periods of rising markets. The authors also detect the presence of herding during stock market crisis of 1999, but after 2002 herding behavior disappears due to the regulatory and institutional reforms in the market and wider participation of foreign investors into the market. Economou *et al.* [76] test the herding behavior in the same market by using CCK [58] method for the 2007-2015 period which covers the sovereign debt crisis. Herding is stronger in small stocks, down markets, high volume and high market volatility days. The crisis in the second

analysis is longer in duration and has severe effects on the Greek economy and this may explain the difference between the two analyses.

Tan *et al.* [77] examine herding behavior in Chinese stock markets between July 1997 to December 2003. The Chinese stocks are dual listed A-share stocks and B-share stocks and all of them are traded in Shanghai and Shenzhen markets. A-share stocks are mostly traded by domestic individual investors and B-share stocks are traded by foreign institutional investors. The authors find evidence of herding by using CCK [58] methodology in daily, weekly, and monthly time intervals but herding becomes weaker with an increase in data frequency. Herding is present for both A-share and B-share markets. Herding in Shanghai A-shares is higher when markets are rising, and also when volume and volatility are high. However, there is no evidence of asymmetry in investor behavior in B-share stocks. This difference is related to the different characteristics of investors trading in these markets. Fu and Lin [78] repeat the same analysis for the 2004-2009 period and find weak evidence of herding for low turnover stocks in downward markets. Demirer & Kutan [79] analyze herding in 375 Chinese stocks by using CH [27] and CCK [58] measures for the period January 1999-December 2002. By using both firm and sector level data, no evidence of herd formation is found. The differences in these estimations may arise from selecting different stocks in the analyses.

The researchers also test for evidence of herding in multi-country studies. Biasco & Ferreruela [80] test the presence of herding in Germany, the United Kingdom, the United States, Mexico, Japan, Spain and France. They restrict their analysis to familiar stocks that are heavily traded within each market. The information about familiar stocks is available to all market participants and it is argued that any herding behavior will be motivated by intentional purposes. The data covers the period of January 1998-April 2004 and they test for herding by using CH [27] and CCK [58] measures. The results show that

herding behavior exists only in the Spanish market and the other markets behave according to the rational asset pricing predictions. Chiang and Zheng [81] study the herding behavior of 18 countries that are divided into three groups which are advanced (Australia, France, Germany, Hong Kong, Japan, the UK, and the US), Asian (China, Indonesia, Malaysia, Singapore, South Korea, Taiwan, and Thailand) and Latin American (Argentina, Brazil, Chile, and Mexico) countries. The authors apply CCK [58]'s methodology to daily data from May 1988 through April 2009 and find evidence of herding except the US and Latin America. These findings contrast with the findings of the previous works that show a lack of herding in Hong Kong ([58]) and China ([79]). The authors explain the difference in herding behavior between Asian and Latin American markets to the greater tendency of investors in Asian markets to follow the news and form their investment strategies based on the signals coming from the US markets. This explanation is supported by the evidence of market conditions in the US market affecting the herding behavior in national markets. The authors also analyze herding in crisis periods 1994 Mexican and 1999 Argentinean crises and find that herding behavior gets stronger in the country that the crisis starts and then produces a contagion effect and spreads to the other countries during the crisis. Economou *et al.* [82] test for herding behavior by using CCK [58] measure for Portuguese, Italian, Spanish and Greek equity markets for the period January 1998- December 2008. The authors find evidence of herding in Greek and Italian markets. Herding behavior in Greece is significant on days when the market is up and down, but only on days when the market is down for Spain. The authors also identify a high degree of positive correlation in the cross-sectional returns' dispersion across these four markets and they argue that herding forces act simultaneously across these markets. De Almedia *et al.* [83] study herding behavior for Brazil, Argentina, Chile and Mexico from January 2000 to September 2010. The authors

first use CH [27]'s methodology and fail to find any evidence of herding. Then they use CCK [58]'s methodology and find evidence of herding only in Chile. Herding in Chile exists during periods of price rises, high trading volume and both low and high volatility.

Indars *et al.* [84] study the herding behavior in the Russian equity market for the period 2008-2015. By using CCK [58]'s methodology, evidence of herding is found during the subprime crisis and Crimea's annexation. The authors argue that the market structure and market conditions in terms of oil prices, liquidity, and market returns are important in determining the existence and the extent of the herding behavior.

The frontier markets also draw the attention of researchers working on herding towards the market. The characteristics of these markets prompt the investors into herding formation. These markets are financially less developed, small in market size with low liquidity. The lack of financial training among most investors, higher informational uncertainties, low transparency and lack of proper institutional designs and regulations create an ideal environment for herding. Arjoon & Bhatnagar [85] investigate herding behavior in Trinidad Tobago Stock Exchange between 2001 and 2014 by using CCK [58]'s methodology. Strong evidence of herding is found especially in small-size stocks and both in rising and falling markets. The results also indicate an increase in herding behavior when liquidity and volatility in the market increase. Güney *et al.* [86] test for herding in eight African markets for the 2002-2015 period. The markets in the analysis are Botswana, Ghana, Kenya, Namibia, Nigeria, Tanzania, Zambia and Bourse Regionale des Valeurs Mobilières (BRVM). BRVM is the regional stock market for Benin, Burkina Faso, Cote d'Ivoire, Guinea-Bissau, Mali, Niger, Senegal, and Togo. By using CCK [58]'s methodology, significant herding evidence is found in all of these markets and herding is stronger in small stocks. Vo & Phan [87] study herding for the Vietnam stock market between 2005-2015. The authors employ CCK [58]'s methodology and identify

significant herding for the period. The herding level is found to be higher in down markets than up markets. Economou [88] examines herding in four Balkan countries, Bulgaria, Croatia, Romania and Slovenia from 2000 to 2016. CCK [58]’s methodology is applied and herding behavior is detected only in Romania. Romania’s greater financial development compared to the other three countries lead to a greater foreign investor participation in the market and this may lead to a herding behavior.

Kallinterakis & Wang [21] investigate herding behavior in the cryptocurrency market for the December 2013-July 2018 period by using CCK [58]’s methodology. Strong evidence of herding in the market is detected in up market days, low volatility, and high-volume days. The evidence of herding behavior in smaller cryptocurrencies is higher which can have destabilizing effects on the market. Vidal-Tomas *et al.* [22] first employ CH [27]’s methodology between 2015 and 2017 and fail to find any evidence of herding. Then, they apply CCK [58]’s methodology to the data and find evidence of herding in down markets. The authors also identify the herding of smaller altcoins with the largest digital coins. Since the information about smaller altcoins is low, the investors give their trading decisions based on the movements of the largest coins.

Hwang & Salmon ([11], hereinafter HS) propose a state-space model of herding measure based on the deviations from the CAPM prices and apply it to US and South Korean stock markets for the period January 1993 to November 2002. The authors find evidence of herding towards the market portfolio both in up and down markets. Macroeconomic factors fail to explain this herding tendency. The sample period covers both Asian and Russian crises and herding disappears during these crises. This evidence contradicts the general belief that suppressing own private information, and herd behavior is more prevalent during the crisis periods. Demir & Solakoglu [89] use this state-space model to test for herding in four Middle Eastern countries (Bahrain, Kuwait, Oman, and

Qatar) for the 2004-2014 period. The results indicate that beta herding exists only in Kuwait and Qatar markets. This difference in herding is caused by the heterogeneity of investors due to religious restrictions in investing equities.

Demirer *et al.* [90] investigate herding behavior at the sector level instead of stock level in the Taiwanese stock market. Their sample period is between January 1995-December 2006. The Taiwanese market is mostly dominated by domestic individual investors who have less professional knowledge and disadvantages in information gathering and processing. The results for the linear model of the cross-sectional standard deviations of CH [27] indicate no evidence of herding. However, the non-linear model proposed by CCK [58] and the state-space model of HS [11] yields strong and significant evidence of herding behavior in the analysis.

The availability of and easy access to the aggregate market data lead to an enormous amount of analyses for different countries, time periods and asset classes. CH [27]'s methodology is not successful in identifying herding towards the market consensus in stressful times. CCK [58]'s test for the non-linear relationship between returns and equity dispersion and HS [11]'s beta herding model are more successful in capturing the herding towards the market consensus. However, each analysis gives mixed results regarding the asymmetries in the herding behavior, like up and down markets, liquidity, volatility, and crisis periods.

2.4.2 Empirical Studies Using Holdings Data Measures

The preliminary empirical studies that use holdings data of institutions, analyze herding behavior in US markets. Lakonishok *et al.* ([23], hereinafter LSV) conduct the first empirical study on herding by using their own measure that is proposed in the same study (Equation (22)). The quarterly holdings data of 779 US pension funds is used for the

period of 1985 to 1989 and a weak herding level of 2.7% is estimated in individual stocks for all active traders. The results are similar for stocks with more than 10 and 20 active traders (2.0% and 2.1% respectively). The results are further analyzed for differences in size and past performance. Herding is found to be greater in small stocks compared to large stocks. The institutions also implement positive feedback trading strategies in small stocks but no destabilizing effects of positive feedback trading strategies are detected.

Grinblatt *et al.* [63] analyze the herding behavior of US mutual funds that implement momentum trading strategies by using the LSV measure. Their sample covers the period of 1975 to 1984 for 274 funds. Their overall herding level of 2.50% is close to the level of Lakonishok *et al.* [23], but a higher level of herding is estimated as the number of active traders increased (4.32% and 5.50% for at least 5 and 10 traders respectively). They also decompose the average herding level into buy and sell herding and herding is identified as higher in buying past winners than buying the past losers. Then the authors analyze an individual fund's tendency to "follow the crowd" or "go against the crowd" by using $SH_{i,t}$ and FH equations denoted in Equation (27) and Equation (28) and find that herding funds have superior performance than the funds that follow contrarian strategies.

Wermers [62] extends the previous analyses above for a longer time period and larger fund base. By using quarterly data for the period of 1975 to 1994 and for all the funds based in the United States, the average LSV measure is estimated as 3.40%, which is slightly higher than the LSV [23] study. The author also states that mutual funds are equally likely to herd in buying and selling stocks. The herding level in growth-oriented mutual funds is higher than in income funds. Since the growth stocks have higher uncertainty about the future earnings relative to value stocks, growth-oriented funds have more motivation to herd compared to income funds. Furthermore, the sell herding level is high in small stocks. The buy herding level is higher in stocks that perform well in the

previous quarter and the sell herding level is also high for stocks that perform poorly, which means that a large part of the reported herding behavior results from positive feedback trading strategies. The main contribution of the paper is, finding out that stocks that funds herd in buying had significantly higher abnormal returns in the following six months compared to the stocks that funds herd in selling. The absence of any return reversal in the following quarters leads to the conclusion that the managers herd on the new information about the future prospects of the companies and this herding behavior is characterized as rational.

Sias [1] investigates the quarterly herding behavior of institutional investors in the US for the period March 1983 to December 1997 by using the measure that is formulated in the same paper. The covariation of institutional trading in each stock in the current quarter with the institutional trading last quarter is estimated. The cross-sectional correlations between the current and the lagged institutional demand are found to be positive and the author decomposes the cross-sectional correlation into institutions following themselves and institutions following others parts. Institutions following others coefficient detects herding behavior and it is positive and significant for a different number of active traders. Then, changes in portfolio weights are analyzed to control whether cross-sectional and time-series correlation in the net flows to institutions result in herding behavior. The buying and selling due to time-series and cross-sectional correlation in the flows to investors is called as “habit investing” and it is concluded that herding is not caused by flows to institutional funds. The evidence of momentum trading is found among institutional investors but herding level is not affected by the momentum trading activities of the institutional investors. The stocks are further divided into market-capitalization quantiles and the evidence of herding is found for both institutions following themselves and others across all size quantiles Institutions following

themselves coefficient is higher compared to institutions following others coefficient which means that institutions distribute their trading decisions across time to reduce trading costs. The author also checks for any return reversal in the future returns but a weak positive correlation between institutional demand and stock returns over the following year is found, which indicates that herding is caused by informational cascades and investigative herding.

Singh [91] examines the behavior of institutional investors in the US for the period 1998-2001 during which the internet bubble and a crash in the markets take place. By using LSV [23] measure, the author finds a high level of herding into internet stocks during the bubble period and momentum trading explains only some part of this herding behavior. The contemporaneous positive abnormal returns with institutional herding during the bubble period become negative abnormal returns when the herding stops. This finding shows that herding behavior is irrational and contributes to the formation of a bubble and then bursting of it.

Popescu & Xu [92] posit that institutional investors that have career concerns, will have a stronger incentive to herd in down markets compared to up markets. They test this hypothesis for US mutual funds for the period of 1983 to 2006 by using Sias [1]'s measure. They find that on average, institutional herding is 40% greater in down markets than in up markets.

The studies mentioned above use changes in holdings for longer time periods. However, Puckett & Yan [93] analyze institutional herding in the US market at weekly frequency for the period 1999 to 2004. By using both LSV [23] and Sias [1] measures, the authors find robust evidence of institutional herding for the sample period. The main contribution of the paper is the identification of strong return reversals following the

short-term sell herds which is motivated by behavioral considerations (investors' fear leads to a sharper decrease in prices compared to a rise in prices when investors are greedy). The evidence of weak return continuation after the short-term buy herd is explained as impounding new information into stock prices and it is concluded to be informative herding.

Choi & Sias [94] investigates institutional investors' herding behavior at industry level instead of fund level in US for the first quarter of 1983 to the fourth quarter of 2005 by using Sias [1]'s measure. They find significant evidence that institutional demand for a stock is positively related with the institutions' lag demand for that stock and their lag demand for other stocks in the same sector. This evidence is consistent with the style investing which indicates a herding behavior due to investors following stocks with specific styles. The findings of the paper also support the investigative herding explanation which arises from institutions following correlated signals. Çeliker *et al.* [95] examine whether mutual funds in the US market herd in industries. They use both LSV [23] and Sias [1] measures to evaluate herding behavior for the period 1980-2013 and document that mutual funds engage herding at the industry level. This herding behavior is not driven by fund flows or style investing. They find evidence of outperformance in industries that are bought by mutual funds in the herding period but no future return reversal is detected in the data.

Jame [96] studies the herding behavior of US pension funds between 1999 and 2008 by using Sias [1]'s measure. The cross-sectional correlation between the fraction of pension funds buying a stock in the previous week this and the fraction buying in the current week is 34.40%. Above 90% of this correlation arises from pension funds following each other. The cross-sectional correlation for small stocks increases to

53.80%. Momentum trading is not a factor in herding behavior. The cross-sectional correlation decreases to 15.19% for quarterly frequency.

Jiang & Verardo [97] investigate the relationship between the herding behavior and skill of the managers in the US equity mutual funds for the period 1990 to 2009. The authors devise a fund-level of herding measure by correlating a fund's trades in the current period with the trading decisions of all other funds in the previous period. By controlling for stock characteristics, significant heterogeneity in herding tendency across funds is detected. Some of the funds follow the others and some of the funds act like contrarians. The differences in herding tendency across funds have predictive power for the cross-sectional pattern of returns. The authors identify a negative relation between herding behavior and mutual fund returns. The top decile herding funds' returns underperform the bottom decile anti-herding funds by an average of 2.28% on an annual basis. The authors provide further evidence that differences in managerial skills are the main reason for this negative relation between herding tendency and fund performance. The anti-herding funds' returns on stocks that are not a part of the institutional crowd trading are higher, which indicates better stock-picking abilities of anti-herding fund managers. During periods of high idiosyncratic risk, anti-herding funds outperform herding funds significantly. This finding is an evidence of anti-herding funds' managers ability to exploit advantageous opportunities in the markets. The over-performance of anti-herding funds persists for up to two years and this persistence eliminates the chance factor in the over-performance. Lastly the authors show that the trades of anti-herding funds anticipate the trades of the herding funds which is interpreted as skillful managers receiving information earlier than the unskillful managers.

Jiao & Ye [98] investigate whether hedge funds herd and whether mutual funds follow and herd after the hedge funds in the US. Significant hedge fund and mutual fund

herding behavior is found by using LSV [23] measure for the first quarter of 2000 to second quarter of 2007. The main contribution of the paper is analyzing whether mutual funds follow and herd after hedge funds. The authors find strong evidence that mutual funds' herding is positively related to last quarter's hedge fund herding while hedge fund herding is not related to last quarter's mutual fund herding. There is also a significant price impact of mutual fund herding on prices in the current quarter and price reversal in the next quarter which has a destabilizing effect on the market. The authors reach to the conclusion that the mutual fund herding behavior arises from reputational concerns.

Choe *et al.* [99] is the first paper that uses LSV [23]'s method for a market outside the United States. They analyze the trading behavior of foreign investors in Korean stocks on a daily basis starting from November 30, 1996 to the end of 1997. They find evidence that foreign investors tend to herd and implement positive trading strategies before the financial crisis of 1997. However, this tendency disappears with the start of the crisis and the evidence of the destabilizing effect of foreign investors in the market does not exist.

Walter & Weber [100] investigate the herding behavior of the mutual funds in Germany for the period from 31 December 1997 to 31 December 2002. The overall level of herding is estimated 2.67% for all active traders. The herding level increases to 5.11% for stocks that have minimum 2 or more traders. The herding behavior is more for larger stocks compared to small stocks and investors employ momentum strategies. The major contribution of this study is the detection of spurious herding attributed to changes in the benchmark index composition. DAX 30 is the major benchmark index used for performance evaluation. When a stock is decided to be included (excluded) from the benchmark index, then investors will buy (sell) the stock for minimizing the tracking error. The authors find a herding level of 22.38% for stock-periods that have changes in the DAX 30 index. The authors also investigate the relationship between herding level

and a high geographic concentration of mutual funds in a certain area. 50% of the funds in the sample are located in Frankfurt and this clustering may ease the mimicking the actions of the other investors. The herding level for funds located in Frankfurt is found to be greater than the herding level for funds located outside the Frankfurt area. Lastly, the authors ask whether large funds have less tendency to exhibit herd behavior because their confidence may be high due to their greater research resources. No evidence of fund size on herding is found. Kremer & Nautz [101] examine the differences in institutional herding results for daily and quarterly data for the German market. By using both LSV [23] and Sias [1] measures, daily and quarterly herding levels are calculated and herding is found to be higher in quarterly measurements. Herding is more pronounced in small stocks for the quarterly data, but for the daily data herding in large stocks is identified. Kremer & Nautz [102] use the same data in the above study to determine the causes and consequences of herding behavior. They identify higher herding in DAX30 stocks and interpret it as unintentional herding driven by identical reaction to public information. By using panel econometric analysis, they further identify that volatility affects herding asymmetrically. Sell herding increases as volatility increases but buy herding decreases as volatility increases. They attribute this asymmetric volatility effect as “unintentional and driven by the common reaction to standard risk measures that force regulated traders to sell high-volatility stocks and to buy those with low volatility.”

Wylie [65] investigates herding behavior among 268 UK equity mutual funds for the period January 1986 to December 1993. The average LSV [23] measure is calculated as 2.6% for the period which is close to the findings of the studies for the US market and it increases with the number of traders. The author also detects a higher level of herding for small and large stocks. There is no significant herding at the industry level. While previous studies find herding related to positive feedback trading strategies in the US

markets, the UK mutual funds are found to undertake contrarian trading (negative feedback trading) strategies. The author claims that this difference occurs due to higher control of mutual funds in the UK equity market compared to the US (70% to 43%). Blake *et al.* [103] search for evidence of herding in UK's pension fund assets over the period of 1987-2012. A strong evidence of herding is documented both in asset classes and subgroups of funds defined by size and sponsor type by using both LSV [23] and Sias [1] measures. The results show that funds managed by the private sector follow other private sector funds and the funds managed by the public sector follow other public sector funds. The authors also find that pension funds follow pension funds that have similar sizes. The results rule out herding due to habit investing, momentum and cascades. They observe strong short-term portfolio rebalancing and small cross-sectional discrepancies in the performance of funds and closet indexing is inferred as the main cause of the herding.

Bonetti [104] studies herding behavior in the equity holdings of Dutch pension funds for the period January 2009- December 2018. By using Sias [1]'s measure, herding among pension funds is detected. The main contribution of this paper is identifying the extent to which an individual fund follows other funds into and out of the same securities over time by estimating the contribution of all other funds' current demand in explaining each pension fund's future demand. The author then analyzes performance of funds that herd more and finds out that these funds underperform the funds that do not herd by 1.32% on annual basis. The small-sized pension funds and funds that trade less tend to herd more. The author also finds evidence of higher herding in stocks that are trading in markets that have high information asymmetries like emerging markets. The underperformance of funds that have a higher herding tendency is inferred as herding driven by reputational concerns.

Arouri *et al.* [105] search for evidence of herding for French equity mutual funds for the period 1999 to 2005. By using LSV [23] measure, the authors identify strong herding for small-capitalization firms. French equity funds buy the past winners but do not sell the past losers significantly. They find that herding is higher for foreign stocks (from countries other than EU-15) compared to French or EU-15 stocks. This finding indicates that the herding tendency of investors increases when public and private information becomes more difficult to obtain. Merli & Roger [106] use the LSV [23] measure to analyze herding behavior of French individual investors for the period of January 1999 to December 2006. They find evidence of herding among individual investors, herding among male investors is higher than among female investors and as the sophistication of the individual trader increases, the tendency of herding decreases.

Agudo *et al.* [107] investigate the herding behavior of the Spanish mutual funds for the period of July 1994 to June 2002. They first categorize funds into management styles of value, growth, and cash. After that, they calculate the monthly LSV herding measure for buying and selling activities of funds in each management style. Their calculated measure is very high on average and among the three management styles, value style funds have a higher herding level compared to growth style funds. This evidence is contradictory to the findings in Wermers [62] but the authors do not delve into the details of this contradiction. Andreu *et al.* [108] repeat the analysis to find evidence of herding in strategic allocations of Spanish pension funds from April 2000 to December 2007. Their average LSV herding measure is calculated as 17.5%, which is higher than the herding measure of mutual funds. There is also evidence of higher buy herding than sell herding, which is in line with previous works ([65]; [109]). There is no significant difference in the average herding levels calculated for increasing and decreasing markets. Herding level is significantly higher in low volatility periods which is also found in the

study of Lobao & Serra [109]. Gavriilidis *et al.* [110] investigate the institutional investor herding of the Spanish funds at the industry level to determine whether it is intentional or spurious herding. By using Sias [1]'s measure for the period of June 1995 to September 2008, they identify significant herding behavior at the overall market level. The herding level is higher when the analyzed industry is underperforming, has high volatility and higher volume. The findings are interpreted as intentional herding motivated by informational and reputational concerns.

Lobao & Serra [109] use quarterly holdings of 32 mutual funds in Portugal between 1998 and 2000. The calculated LSV measure for the period is 11.38% which is higher than the previous studies of developed markets. Higher herding in less developed markets is in line with models of informational cascades or reputational concerns. Herding is also low when the market returns are high and volatility is low which is interpreted to be consistent with the information-based explanations. The authors claim that investors feel more confident and use their own information when the returns are high. The high volatility in the market is expected to increase the uncertainty and herding behavior, but the authors state that if volatility increases due to new unexpected information and investors' reaction to this new unexpected information is slow, then this may lead to lower levels of herding. The drain of liquidity in volatile times may also cause a negative relationship. Gavriilidis *et al.* [111] use Sias [1]'s measure to examine institutional herding in Portuguese equity mutual funds for the July 1996-June 2011 period. Portugal's equity market is considered as a concentrated market and the authors investigate the interaction with institutional herding and several different styles (momentum, analysts' recommendations, value-growth, size, volume, and volatility). Institutional demand for the current month is related significantly to the previous month's institutional demand and this positive relation is mostly driven by institutions following

others. All of the styles that are investigated have no effect on explaining the persistence of institutional demand. The authors conclude that style-investing is not a generally applied strategy in a concentrated market and does not have any effect on herding behavior.

There are also various studies that analyze herding behavior in emerging markets. Batra [112] analyses the herding behavior of foreign institutional investors in India for the period January 2000 to December 2002. The previous studies use low-frequency data to measure herding, but in this paper daily and monthly data are used. The average LSV [23] measure is 9.41% daily and 14.72% for monthly samples which indicate a high level of herding among foreign institutional investors. The author does not find any evidence of destabilizing effect of this herding for the corresponding period.

Bowe & Domuta [113] investigate the herding behavior of both foreign and domestic institutional investors in Indonesia for the period January 1997 to December 1999 by using LSV [23] measure. They divide the sample period into pre-crisis, crisis and post-crisis parts for Asian crisis and find different behavior of herding for these periods. Foreign institutions have a higher herding tendency compared to domestic institutions in all the periods and their herding activity increases in the crisis and post-crisis periods. Domestic institutions' herding levels decrease in the crisis and after the crisis. They also detect foreign herding in small stocks but domestic investors' herding is positively correlated with firm size.

Voronkova & Bohl [114] analyze herding behavior among Polish pension funds for the period 1999 to 2002 and computes the LSV measure of 22.6%. This high finding is attributed to the highly regulated and concentrated structure of the Polish pension fund system. Herding behavior is higher in the small stocks and the funds implement positive

feedback trading strategies but these strategies do not create any destabilizing effects in the market.

Chen *et al.* [115] investigate the herding behavior of foreign institutions in Taiwan for the period January 2002 to December 2006 by using Sias [1]'s measure. They classify the stocks into different industries and find evidence of a high cross-sectional correlation between the institutional demand in the current period and lagged institutional demand for the whole industries. But the high correlation emanates from institutions following themselves rather than institutions following others. Herding in industries that have high past returns and large market capitalization is also considered as investigative herding. Hung *et al.* [116] analyze herding behavior in Taiwan for the period December 1995 to December 2006. By using Sias [1]'s measure, the authors find evidence of institutions following themselves instead of following others in their trading activity. Herding behavior is stronger in buying underpriced stocks with lower liquidity, lower prior returns, lower market-to-book ratio, and small in market capitalization. Furthermore, the evidence of return continuation after the buy herding is interpreted as a sign of investigative herding but evidence of return reversal after sell herding indicates irrational herding behavior. Fang *et al.* [117] use Sias [1]'s measure to explore the herding behavior of foreign institutional investors in the Taiwan equity market from January 2002 through December 2010. They first detect that herding behavior is caused by cascades instead of habit investing and momentum trading. Then, the analysis is extended by using a panel smooth transition regression model and the results of the model indicate that foreign institutional investors' negative cascades are found in their largest net buying of equities, but their positive cascades are identified in the small-capitalization and winner stocks.

Raddatz & Schmukler [118] look for evidence of Chilean pension funds herding behavior at a monthly frequency for the period 1996 to 2005 by using the LSV measure.

They investigate herding levels for different asset classes like equities, corporate bonds and government bonds. They find that herding is more prevalent in corporate bonds, followed by equities and government bonds. This evidence is interpreted as there is a higher tendency to herd in instruments that are more opaque informationally and asset class characteristics are important in determining the level of herding. Herding is higher in funds that compete with each other which is indicating herding for reputational concerns.

Venezia *et al.* [119] examine herding behavior in Israel for the period January 1994 to December 1997. They use LSV [23] measure to calculate the herding behavior of professional and amateur investors. They find both groups of investors herd but the herding tendency of amateurs is higher than the professional investors. They infer amateur herding can be resulted from information search or from a higher tendency to behave irrationally. The professional investors' compensation in the sample is not benchmarked to a specific market index, so their herding is motivated by information search theory. The herding level decreases as the firm size increases. They find that the herding behavior of amateurs causes higher market volatility, which is interpreted as a serious threat to market stability.

Economou *et al.* [120] examine the herding behavior of institutional investors in Bulgaria and Montenegro equity markets between 2005 and 2012. The authors find evidence of higher herding in these two markets compared to markets in developed countries. The authors examine herding for different market states and find evidence of herding behavior during the positive market performance and high volume in both markets.

Choi & Skiba [121] investigate herding in an international context. They use equity holdings data from 41 countries to calculate Sias [1] measure without the decomposition for the period starting from the last quarter of 1999 to the first quarter of 2010. They find evidence of institutional herding that is economically and statistically significant for 34 countries. The average cross-sectional correlation between current institutional demand and lag institutional demand for stocks is 17.94 %. The herding measure of developed countries is higher relative to emerging markets which contradicts the findings in the previous works (20.21% for developed countries, 14.29% for developing countries). They also control for the momentum effect on herding behavior. Institutional investors in 31 countries are implementing momentum strategies but herding coefficients remain significant. They further check whether herding has any destabilizing effect in the data and find evidence of a positive correlation between institutional demand and current return and positive to no correlation between institutional demand and future returns. This evidence is interpreted as herding based on information, which can be categorized as cascades or investigative herding. They examine the herding propensities and the information environment in these markets to make an inference between the two possible explanations. Stock market development, corporate transparency, ease of access to information, investor independence, and macroeconomic factors are used as proxies of information asymmetry. If there is a positive relation between herding and information asymmetry, then the herding is caused by information cascades because institutional investors herd more in less transparent markets since information is uncertain. If there is a negative relation between herding and information asymmetry, then the herding is spurious or investigative because institutional investors herd more in more transparent markets since information is easily accessed. The results indicate a negative relation

between herding propensity and information asymmetry and investors herd because they are following the same information and signals.

The researchers are also interested in the herding behavior of institutional investors in bond markets. Cai *et al.* [122] investigate herding among institutional investors in US corporate bond market. The authors find a higher level of herding compared to equity markets by using both LSV [23] and Sias [1] measures for the period 2003-2008. Bond herding is higher in small and illiquid bonds similar to herding behavior in equities. Institutions have a buy herding tendency in newly issued bonds and sell herding tendency in bonds that will mature soon. The authors detect an increase in buy herding after bond trading reporting TRACE started data dissemination. Sell herding is negatively correlated with credit ratings, rating changes, and corporate earnings surprises. The authors also find evidence of positive feedback trading strategies and destabilizing effect of sell herding. The evidence of return reversal is mainly found in junk and illiquid bonds. The authors reach to the conclusion that buy herding is caused by cascades and sell herding is driven by reputational concerns.

Oehler & Chao [123] study the institutional investor herding in the German bond market for the period 1993 to 1995. By using LSV [23] measure, they find a weak level of herding (2.60%) among German mutual funds trading in the bond market compared to the herding level in equity markets. This result is attributed to the big variety of bonds that the investors can choose among compared to the limited equity universe.

Koetsier & Bikker [124] analyze the herding behavior of Dutch pension funds in sovereign bonds market during a financial crisis that covers the period December 2008-December 2014. They estimate the buy and sell herding measures of 0.14, 0.12 and 0.16 by using the LSV [23] measure monthly. They find out country-specific factors play role

in herding behavior. The buy herding for safe heaven bonds exceeds sell herding significantly but there is no significant difference in buy and sell herding of European crisis countries for the whole period. When they narrow the time period for the crisis period, they detect a higher buy herding level in safe heaven bonds compared to bonds of crisis countries, and higher sell herding in crisis countries relative to sell herding in safe heaven bonds. The analysis reveals that macroeconomic factors and country-specific financial market conditions are the main drivers of herding behavior. The higher herding level during the crisis period is interpreted as evidence of herding due to reputational and career concerns.

Nofsinger & Sias [10] use changes in the fractional institutional ownership and individual ownership to detect herding behavior in New York Stock Exchange (NYSE) for the 1977-1996 period. The fractional institutional ownership is defined as the ratio of number of shares held by institutions to the number of shares outstanding. The fraction of shares held by individual investors is calculated as one minus the fraction that is held by institutional investors. Their main difference from the previous works, is including the herding of individual investors to the analysis and using fractional institutional ownership, which controls for changes in stock dividends and stock splits. The authors document a high positive contemporaneous correlation between changes in institutional ownership and stock returns. The possible reasons for this strong correlation are stated as higher positive-feedback trading of institutional investors compared to individual investors and higher impact of significant herding behavior by institutional investors on prices compared to the impact of herding by individual investors. They also identify that changes in institutional ownership positively correlated with lag returns but they do not find any evidence of return reversal in the sample. Iihara *et al.* [125] apply the same methodology as Nofsinger & Sias [10] to examine the herding tendency of individual,

institutional, and foreign investors in Japan for the period 1975-1995. The authors find a strong positive relationship between annual changes in ownership and herding period returns for institutional and foreign investors. This result implies that institutional and foreign investors implement positive feedback trading strategies or their trades impact stock prices more than the individual investors. The finding of subsequent return reversals in institutional investors' herding is considered as evidence of herding driven by non-informational motives. However, no destabilizing effect of foreign investors is detected in the future returns. Li & Yung [126] test the same methodology in American Depository Receipts (ADR) market between 1985 and 1998. The results indicate a strong positive relationship between changes in institutional ownership and ADR returns. This strong positive relation persists after controlling for the momentum effect, and no evidence of future return reversal is found.

The empirical studies that use holdings data of the institutional investors show that there is a tendency to herd among institutional investors in general. However, this herding tendency changes from market to market. The herding behavior is higher in less developed markets compared to developed markets due to the opaqueness of the market informationally. The foreign investors tend to herd more than the domestic investors and there is an asymmetry in herding behavior under different market states. It is hard to differentiate among different herding theories by using the proposed measures.

2.4.3 Studies Using Turkish Market Data

I have focused mainly on the international articles that are mostly originated in the U.S in the above sections. Since I am interested in analyzing the herding behavior in the Turkish markets, the researches that study the herding behavior in the Turkish markets

will be reviewed in this section. The studies that use aggregate market data will be reviewed first. Then, the studies that use holdings data will be reviewed.

Altay [127] tests herding behavior for all stocks in BİST for the period January 1997- February 2008 by using aggregate measures. The author first use CH [27] measure on a daily frequency, but cannot find evidence of herding in the market. The extreme tails of the market return distribution are determined to be 1% and 5% and the coefficients of the regressions are estimated as positive which are in line with the prediction of rational asset pricing models. Then, the author tests for the non-linearity in the cross-sectional dispersion of equity returns by using the CCK [58]’s methodology and detects negative coefficients for the second term of the regression in Equations (13) and (14). This finding is interpreted as evidence of herding behavior in BİST. Lastly, the author uses HS [11]’s methodology to test for herding behavior. The cross-sectional variance of the estimated betas is predicted as decreasing, which indicates evidence of herding towards the market portfolio.

Kapusuzoğlu [128] studies the existence of herding behavior in BİST 100 stocks between January 2000 to January 2010. CCK [58]’s methodology is applied by using daily returns for the period and non-linearity in the cross-sectional deviations of stock returns is detected both in extreme rising and falling market days. Investors engage in herding behavior instead of rational investment behavior.

Solakoğlu & Demir [129] search for herding behavior in BİST for the period of 2000 to 2013. The authors use HS [11]’s methodology to search for evidence of sentimental herding in BİST 30 index and Second National Market stocks. Investors in stocks of BİST 30 index are defined as informed who have access to the maximum amount of information and resources. However, the investors of stocks in the Second

National Market are defined as uninformed because they are mostly local investors with a higher level of information asymmetry and smaller assets. The findings indicate that there is not any evidence of herding behavior in BİST 30 stocks but herding exists for stocks that are traded in the Second National Market.

Balcılar & Demirer [130] examine the dynamic relationship between global risk factors and herd behavior in the Turkish equity market for the period January 2000-March 2012. The authors transform the cross-sectional average dispersion statistic of CCK [58] into “a time-varying transition probability Markov-switching model where regime transitions are modeled as a function of domestic market volatility, and global risk factors such as S&P 500 index, USD/TRY exchange rate and CBOE S&P 500 volatility index (VIX).” By adapting this methodology, the authors try to estimate the effect of global shocks on the herding regimes in Turkey. The market regimes are identified as low, high and extreme volatility. Then the authors find evidence of herding behavior only in high and extreme volatility states. Çakan & Balagyozyan [131] apply CCK [58]’s methodology to Turkish banking sector stocks for the period 2007 to 2012. The authors identify an asymmetric herding behavior that exists only in rising markets.

Doğukanlı & Ergun [132] utilize the state-space model of HS [11] to investigate herding behavior in BİST for the period January 2000 to November 2011. The herding behavior is present for both daily, weekly, and monthly frequencies. Herding behavior is found to be stronger in financial stocks than industrial stocks.

Ergun & Doğukanlı [133] test for herding behavior in BİST between January 2000 and September 2012. The cross-sectional dispersion of stock returns is computed by using CH [27]’s methodology for different sectors. The results indicate no evidence of herding.

Özsu [134] investigates the herding behavior in BİST 100 index stocks for the period 1988-2014. The author first uses CH [27] methodology and cannot find any evidence of herding which is in line with the results of the previous works. Then CCK [58] methodology is utilized and the results do not indicate non-linearity in the cross-sectional standard deviation of returns. This result indicates that herding behavior does not exist which is contradictory to the findings of the previous works. Lastly, HS [11]'s methodology of cross-sectional volatility of beta coefficients is employed for detecting herding behavior. The market return, the market volatility, and the size and book-to-market factors of Fama-French are also taken into consideration to determine whether herding is intentional or spurious. The results indicate that herding behavior exists in the sample and it is intentional because the herding coefficient remains significant after adding market return and market volatility. Including Fama-French size and value factors to the analysis reveal that there is a negative relation between herding and stock size. The author repeats the same analysis for the first session and the second sessions of the day separately. The results show that herding behavior is stronger in the second session of the day compared to the first session of the day.

Gavrilidis *et al.* [135] investigate positive mood during Ramadan and herding behavior in Turkey with six other Muslim countries. CCK [58]'s methodology is used for measuring herding behavior between January 1990-February 2014. The results indicate the presence of herding within and outside Ramadan in Turkey. The herding is stronger during the Ramadan days and also exists both in up and down-market days. The evidence of herding is present in market's volume rising and falling days during Ramadan. The herding estimations are conditioned upon daily movements of the S&P 500 index and VIX. The conditioned herding in Turkey is estimated to be significant for up and down days of these two variables.

Akinsomi *et al.* [136] analyze herding behavior in REITs in BİST between January 2007-May 2016. CCK [58]'s methodology of cross-sectional absolute deviations of returns is used and evidence of herding is found in the REITs. The herding behavior exists both in low and high volatility periods while the herding behavior is stronger and shorter in duration for high volatility periods compared to low volatility periods. Informational asymmetries between investors in the market, difficulties in the appraisal of real estate and net asset value discounted pricing in REITs are considered as possible explanations for the formation of the herding behavior in the analysis.

Dalgıç *et al.* [137] contribute to herding literature by analyzing intraday and daily herding tendencies of different types of investors in BİST 100 stocks. The data covers the period from June 2013 to May 2014. The investors are classified as individual-corporate investors, brokerage houses, and mutual funds. The individual-corporate investors are defined as the most unskilled type in the analysis. The cross-sectional dispersion of trading volume is used as an inverse proxy of herding behavior. The authors argue that low dispersion of trading volume across different stocks represents a high level of herding towards the market. The analysis shows that individual and corporate investors herd more than the brokerage houses and mutual funds. Brokerage houses herd mostly in small stocks but mutual funds mostly herd in large stocks. Sell-side herding is greater than buy-side herding and investors tend to herd more in market downturns relative to market upturns. There is no evidence of macroeconomic or firm-specific news announcements' effect on herding behavior.

Somuncu & Karan [138] investigate the herding behavior of both domestic and foreign institutional investors in BİST for the 2001-2004 period. By using LSV [23] methodology on a monthly basis, they calculate herding measures as 35.72% for foreign investors and 10.34% for domestic investors. The results are significant and shows a high

level of herding behavior for the period. The sample period covers the financial crisis of 2001 and the high level of herding can be caused by this crisis. They also search for evidence of positive feedback trading strategies and find it for domestic investors. The results indicate that foreign investors implement negative feedback trading strategies. Durukan *et al.* [139] is the second study that utilizes LSV [23] methodology in the Turkish equity market. The authors investigate the herding behavior of foreign investors between January 2006 and December 2015. The average herding measure for the whole period is 3.6% while it decreases to 1.3% for the crisis period of October 2008 – April 2009. The decrease in herding in the crisis period is explained by the effect of lower trading by foreign investors in that period. The herd behavior conditioned on size is also tested and the authors find evidence of a higher herding tendency in small stocks. Evrim *et al.* [140] investigate the herding behavior of 18 equity mutual funds in Turkey for the period from March 2014 to April 2017. LSV [23]’s measure is employed for monthly holdings of these mutual funds. The average herding for the period is found to be 0.02 and buy herding is stronger than sell herding in the data.

Alemanni & Ornelas [141] investigate the herding behavior of foreign investors in Turkey with eight other emerging markets for the period of 2000 to 2005. They use buying volume of the market divided by the total foreign turnover in the market, instead of counting the number of funds buying stock divided by the total number of funds trading that stock in LSV [23]. The result of this adapted measure is 3.63% for Turkey.

Turkey is one of the countries herding behavior is investigated in Choi & Skiba [121]’s study. The cross-sectional correlation between the institutional demand in the current quarter and the previous quarter calculated by Sias [1]’s methodology for the period fourth quarter of 1999 to the first quarter of 2010 is %15.98 and it is significant. The cross-sectional correlation decreases to 9.70% when momentum strategy is included

in the analysis. The authors identify a positive correlation between current institutional demand and returns for the current period. However, institutional demand is not related to stocks' future returns which means that herding does not have any destabilizing effect in the Turkish market.

Gavriilidis *et al.* [142] investigate the relationship between investor mood and herding of domestic mutual funds in Turkey. The weekend effect, holiday effect, Ramadan, and sunshine are used as proxies of mood in the analysis. The sample spans the period of January 2002 to August 2008. The authors use Sias [1]'s methodology to estimate herding behavior on a daily frequency and find evidence of herding in the data. The cross-sectional correlation between institutional demand today and institutional demand yesterday is positive and significant for a different number of active traders. The herding measure which is derived from the decomposition of funds following the trades of other funds is positive and significant. The herding level increases as the number of active funds per stock increases. Buy herding is found to be stronger than sell herding. However, the authors cannot find evidence of relation between herding and mood in the analysis.

The empirical studies of herding in Turkey mostly use aggregate measures due to ease of getting data. The studies that use holdings measures are limited and studies that use Sias [1]' methodology do not focus on the causes of the herding behavior. As it is easily seen, the herding behavior of institutional investors has not been detailly investigated in the Turkish markets. In subsequent chapters, my goal is to fill this gap by analyzing the institutional herding in the Turkish stock market by using Sias [1]'s methodology.

CHAPTER III

HERDING OF DOMESTIC INSTITUTIONAL INVESTORS IN BORSA ISTANBUL

3.1 Introduction

Institutional investors are considered as sophisticated and more rational compared to individual investors and they are one of the most important pillars of financial markets. They have more resources to process information and to give financial decisions. They are also assumed to prevent the divergence of prices from the fundamental values by trading against the noise traders. The importance and influence of institutional investors have increased in the world. The institutional investors' assets under management reach to \$61 trillion in the world ([143]). The size of the institutional investors and their influence is also increasing in the Turkish markets.

There are mainly two types of domestic institutional investors in Turkey. These are mutual funds and pension funds. The Capital Markets Law was approved in 1981 and the first mutual fund in Turkey was established in 1986 ([144]). The Individual Pension Savings and Investment System Law was legislated in 2001 and the system became operational in 2003 with the approval of the first pension plans ([145]). Figure 2 shows the historical growth of the mutual funds and pension funds in Turkey. The size of the mutual funds and pension funds in 2006 is 22 billion TL and 2.9 billion TL respectively. The total size of the assets is 3.13% of Turkey's GDP. In 2020, total assets of mutual funds and pension funds reach to 132.4 billion TL and 170.5 billion TL. The share of the system

in GDP reached to 6.00% in 2020. The annual growth rate of total assets of mutual funds is 12.71%, and 31.22% for pension funds. The fixed-income stocks heavily dominate the portfolio allocations of these funds. Figure 3 shows the historical change in the allocations to stocks in mutual and pension funds. The total allocation to stocks is 541 million TL (2.46% of all assets) in mutual funds and 232 million TL (8.0% of all assets) in pension funds in 2006. The total allocation to stocks reaches to 16.7 billion TL (12.60% of all assets) for mutual funds and 23 billion TL (13.50% of all assets) for pension funds in 2020.

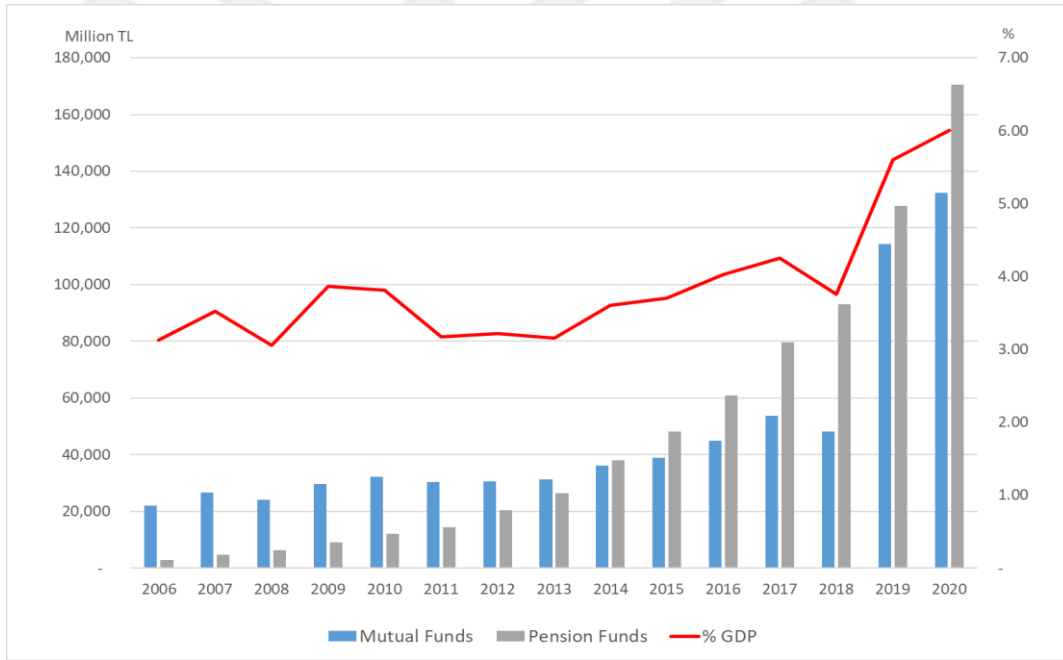


Figure 2: Yearly Growth of Domestic Institutional Funds

This figure shows the assets under management of domestic mutual and pension funds and their share as a percentage of GDP for the period of 2006-2020. (Source: Turkish Capital Markets Association)

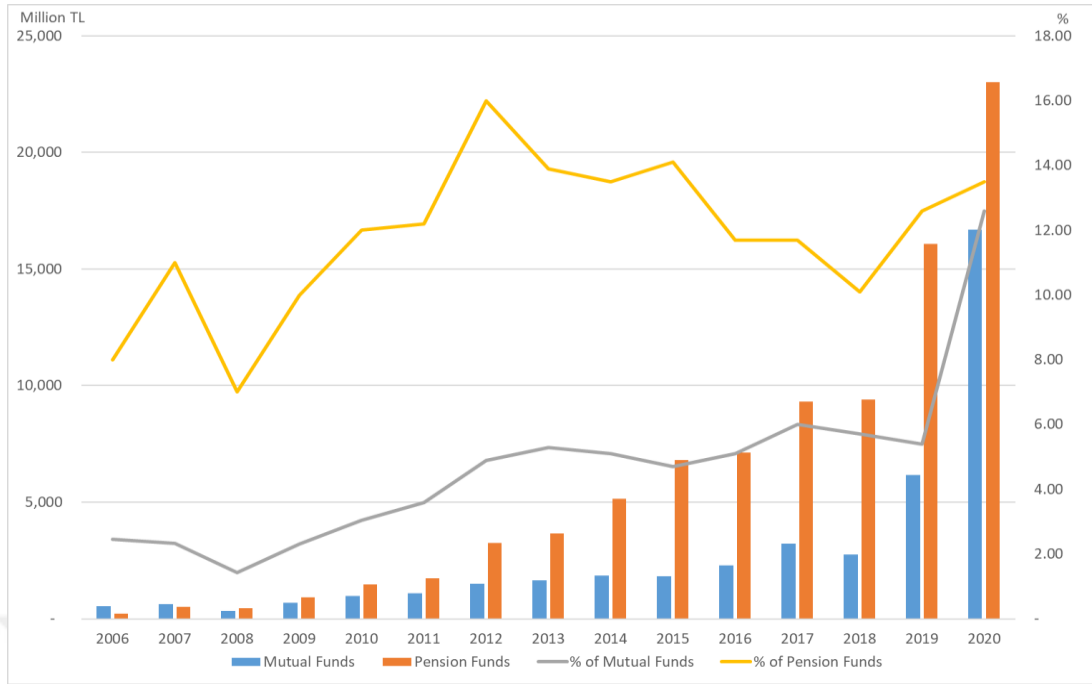


Figure 3: Share of Stock in Domestic Institutional Funds

This figure presents the total stock investments of domestic mutual and pension funds and their percentage shares in all assets for the period of 2006-2020. (Source: Turkish Capital Markets Association)

As the portfolio sizes of institutions grow, their financial decision-making process has started to attract the attention of more researchers. The rationality of institutional investors is disputed and it is argued that institutional investors have several reasons to herd ([23]). These explanations of herding are categorized as informational cascades ([25]; [64]), investigative herding ([29]; [30]), reputational and compensational herding ([24]), characteristic herding ([51]), and fads (Freidman [146]; Barberis & Shleifer [147]). The informational cascades lead to herding behavior when investors ignore their own noisy information and trade in the same way with the others by inferring information from each other's trades. Investigative herding results from the investors' collective buying and selling because of following the same signals. The reputational and compensational herding occurs when investors act in the same way with the herd to avoid facing reputation and compensation costs. The investors may be attracted to stocks that have

specific characteristic and this may create a characteristic herding. Lastly, the investors may herd because of fads and hype. Sias [1] categorizes information cascades and investigative herding as informational herding, and the others as non-informational herding.

The empirical works on institutional herding mainly use two measures. These are constructed by Lakonishok *et al.* ([23]; LSV hereinafter) and Sias [1]. LSV [23]'s measure seeks to find whether more institutions are trading on either the buy or sell side of the market within the specific time period, than would be expected if these institutions traded independently by considering net changes in stock holdings. Sias [1]'s measure also uses changes in net stock holdings of institutions, but it is a dynamic measure that allows for direct observation of the extent to which institutions follow each other over adjacent time periods. LSV [23]'s measure does not allow the decomposition into institutions following themselves and following others. The institutional investors spread out their buy and sell decisions throughout time to minimize the price effects of big size orders. The continuation of buying and selling in the same stocks does not constitute a herding behavior. On the contrary, the collective buying and selling of the institutions in the same stocks throughout time are the real herding behavior and Sias [1]'s methodology allows for the decomposition of trades into institutions following their own trades and institutions following others' trades. This methodology is applied for holdings of US mutual funds in US stocks quarterly in the original paper of Sias [1]. Chen *et al.* [115] examine the Taiwanese stock market, Puckett & Yan [93] analyze US stocks at a weekly frequency, Choi & Sias [94] and Çeliker *et al.* [95] examine herding in US stocks at the industry level, Cai *et al.* [122] investigate herding in US corporate bond market, Blake *et al.* [103] analyze herding in UK pension funds by using the same methodology. Choi & Skiba [121] and Gavriilidis *et al.* [142] studies use Sias [1] methodology for the Turkish

stock market, but these studies do not investigate the causes of herding behavior. My goal is to investigate whether institutional herding exists in the stock market of Borsa İstanbul (BİST) and to explain the causes of herding behavior by following the steps in Sias [1]'s methodology.

The results reveal that the lagged institutional demand is related to the current institutional demand, but this relation is mostly driven by stocks with few institutions. The coefficient of institutions following each other is considered as the herding measure and the results show evidence of herding behavior among domestic institutions. However, this herding evidence disappears as the number of active institutions increases. To determine whether institutional herding is driven by institutions' attraction to stocks with certain characteristics, habit investing is examined. Habit investing is specified as a special case of characteristic herding by Sias [1]. If there is a positive time-series correlation in the net flows of the funds, then investors will adjust their individual stock weights in their portfolios with these net flows. They will buy the stocks in their portfolios when there are inflows and sell from the stocks in their portfolios when there are outflows. These buy and sell activities can be interpreted as a herding activity and Sias [1] controls for it by focusing on the cross-sectional correlation between the fraction of institutions increasing portfolio weights for each stock over consecutive time periods. The results show that herding behavior is not driven by habit investing. Institutional investors implement momentum trading strategies and these strategies can be interpreted as herding behavior if many institutions implement them at the same time. I add lagged stock returns to my analysis and find evidence of momentum strategies for small stocks, but these strategies do not eliminate the evidence of herding behavior. I find evidence of negative feedback trading strategies for large stocks. I investigate the correlation between institutional demand and future returns to check whether institutional demand is creating

any destabilizing effects on prices, but fail to find any evidence of future return reversals. Finally, I sort the stocks in each quarter by market-capitalization and estimate the cross-sectional correlation between institutional demand and lagged institutional demand for five size quantiles. The results show that herding behavior exists in small-size stocks, but there is a contrarian behavior in large stocks. The evidence of significant herding behavior in small-size stocks without any destabilizing effect in future returns lead to the conclusion that domestic institutions' herding behavior is driven by inferring information from each other's trades (informational cascades).

The structure of the paper is as follows. Section 2 describes the data and methodology. Section 3 presents the empirical findings by using LSV [23] methodology. Sections 4 and 5 present the empirical findings for habit investing and momentum trading. Section 6 investigates the relation between institutional demand and returns. Section 7 presents the results of the herding tests for different size quantiles. Section 8 concludes.

3.2 Data & Methodology

The stock ownership data of each mutual and pension fund is obtained from Takasbank. Institutional ownership data spans the period of March 2006 through September 2018, for a total of 51 quarters. Since, I am interested in the herding behavior in domestic stocks, all the foreign stocks, ETF's, warrants, and commodities are deleted from the data. The mutual funds and pension funds are managed by specific institutions. There are different units in the institution, but one portfolio manager can manage several funds at the same time. Also, portfolio managers attend the same investment committee meetings in the company and they use the same research generated within the company. Using stock holdings and trading activities of individual funds can affect our herding measure. To overcome this, I aggregate the funds under the same institution manually by using their

asset management company information in Public Disclosure Platform (KAP). Adjusted stock prices, shares outstanding, and market capitalization data are obtained from EquityRT module of Rasyonet. Panel A of Table 1 shows the number of total institutions and the number of stocks the institutions hold in their portfolios. The average number of institutions for the sample period is 46. The average number of stocks that are held in the portfolios is 207 for the whole period.

The stock holdings of institutions in each quarter may change due to stock dividends and stock splits. These changes do not constitute a real trading activity. For this reason, I calculate, at the end of each quarter, each institutional investor's position in each stock as a fraction of the stock's number of shares outstanding. For each stock and quarter, an institutional investor is defined as a buyer if its ownership in the stock increases and a seller if its ownership decreases. For each stock quarter, the fraction of institutional investors trading the stock that are buyers to the number of actively trading institutional investors is calculated. I denote this ratio as the "raw fraction of institutions buying" stock k during quarter t :

$$Raw\Delta_{k,t} = \frac{No. of institutions buying_{k,t}}{No. of institutions buying_{k,t} + No. of institutions selling_{k,t}} \quad (32)$$

Panel B of Table 1 shows the average number of actively buying and selling institutions for each stock in the data. For all active institutions, there are on average 11 different institutions trading a particular stock. As the number of active institutions increases, the average number of active institutions for each stock also increases and it reaches to 26 for stocks with at least 20 institutions. Panel C of Table 1 shows the average number of stocks traded for different number of active institutions. The average number of stocks traded by all active institutions is 134 and 62.25% of it consists of BİST 100 stocks. As the number of institutions increases, the number of stocks traded decreases and

a higher share of the traded equities consists of BİST 100 stocks. The average number of stocks traded by at least 20 institutions becomes 23 and 99.82% of them are BİST 100 stocks. Panel D of Table 1 shows the average market capitalization of stocks (in billion TL) traded by different number of institutions. The average capitalization is 3.03 billion TL for all active institutions. However, the average capitalization increases as the number of active institutions increases. The average market capitalization of stocks with at least 20 active institutions is 11.87 billion TL for the whole period. As the number of active institutions increases, the institutional investors trade more BİST 100 stocks with higher market capitalizations.

Next, I standardize $Raw\Delta_{k,t}$ by subtracting the cross-sectional average (across K stocks) raw fraction of institutions buying in quarter t and dividing by $\sigma(Raw\Delta_{k,t})$, the cross-sectional standard deviation (across K stocks) of the raw fraction of institutions buying in quarter t. This is defined as the standardized fraction of institutions buying stock k in quarter t, it is denoted as $\Delta_{k,t}$, shown below:

$$\Delta_{k,t} = \frac{Raw\Delta_{k,t} - \overline{Raw\Delta_t}}{\sigma(Raw\Delta_{k,t})} \quad (33)$$

I estimate, each quarter, a cross-sectional (across K stocks) regression of the standardized fraction of institutions buying stock k ($\Delta_{k,t}$) in the current quarter on the standardized fraction of institutions buying stock k the previous quarter ($\Delta_{k,t-1}$):

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t} \quad (34)$$

Since the data is standardized to zero mean and unit variance, there are three possible values for β_t . These are:

- β_t can be equal to zero which means that the standardized fraction of institutions buying stock k in the previous quarter is independent of the standardized fraction of institutions buying stock k in the current quarter. Thus, lagged institutional demand does not affect current institutional demand.
- β_t can be between minus one and zero ($-1 \leq \beta_t < 0$). If this is the case, then institutional investors will sell stocks that were bought in the previous quarter and they will buy the stocks that were sold in the previous quarter.
- β_t can be between zero and one ($0 < \beta_t \leq 1$). In this case, institutional investors will continue to buy stocks that they bought in the previous quarter and they will continue to sell the stocks that they were selling in the previous quarter.

Sias [1] argues that β_t is not an indicator of herding behavior. β_t is further partitioned into two parts by using the decomposition shown below:

$$\begin{aligned}
 \beta_t = \rho(\Delta_{k,t}, \Delta_{k,t-1}) &= \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})} \right] \\
 &\times \sum_{k=1}^K \left[\sum_{n=1}^{N_{k,t}} \frac{(D_{n,k,t} - \overline{Raw\Delta_t})(D_{n,k,t-1} - \overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}} \right] \\
 &+ \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})} \right] \\
 &\times \sum_{k=1}^K \left[\sum_{n=1}^{N_{k,t}} \sum_{m=1, m \neq n}^{N_{k,t-1}} \frac{(D_{n,k,t} - \overline{Raw\Delta_t})(D_{m,k,t-1} - \overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}} \right]
 \end{aligned} \tag{35}$$

where $N_{k,t}$ is the number of institutional investors trading stock k in quarter t and $D_{n,k,t}$ is a dummy variable that equals one (zero) if institution n is a buyer (seller) of stock k in quarter t . $N_{k,t-1}$ is the number of institutional investors trading stock k in quarter $t-1$, $D_{n,k,t-1}$ is a dummy variable that equals one (zero) if institution n is a buyer (seller) of stock k in quarter $t-1$, and $D_{m,k,t-1}$ is a dummy variable that equals one (zero) if institution m ($m \neq n$) is a buyer (seller) of stock k in quarter $t-1$.

This partition helps us in decomposing β_t into institutions following themselves and following others parts. Institutions may follow themselves into and out of the same stocks over adjacent quarters. Since the institutions have huge positions in stocks, their buy and sell decisions in full size may affect the price disadvantageously. To overcome this price effect, institutions generally prefer to trade in relatively smaller sizes to the overall position and they may continue to buy or sell stocks in the following quarter. The first part of the equation gives us the portion of the correlation that results from institutions following themselves. If this coefficient is zero, then institutional investors' transactions this quarter are independent of their own transactions in the last quarter. If this coefficient is positive, then institutional investors are buying or selling the same stock in both quarters. A negative coefficient means that institutional investors are selling the stock that they bought in the previous quarter, or buying the stock that they sold in the previous quarter. The second part of the equation gives us the coefficient that arises from institutions following other institutions. This term will be positive if institutional investors tend to follow each other into and out of the same stocks, that is, investor m buys (sells) stock k in quarter $t-1$ and investor n buys (sells) stock k in quarter t . The positive term will be the evidence of herding behavior. If institutional investors sell (buy) stocks that other institutional investors bought (sold) the previous quarter, this term will be negative. Thus,

the institutional investors are implementing contrarian strategies. If institutional investors' transactions this quarter are independent of other institutional investors' transactions last quarter, this term will be zero.

The first column of Panel A of Table 2 shows the results of the 49 cross-sectional regressions of the standardized fraction of institutions buying stock k ($\Delta_{k,t}$) in the current quarter on the standardized fraction of institutions buying stock k the previous quarter ($\Delta_{k,t-1}$) for all actively trading institutions. The time-series average coefficient of the 49 cross-sectional regressions is 0.2000 and it is significant at the 99.99% level. The coefficient is interpreted as one standard deviation increase (decrease) in the standardized fraction of institutions buying stock k in the previous quarter leads to a 20.00% standard deviation increase (decrease) in the standardized fraction of institutions buying stock k in the current quarter. The coefficients in the regressions of institutional demand on lagged institutional demand are the cross-sectional correlations since the data is standardized and normalized. The second column of Panel A shows the portion of correlation that results from institutional investors following themselves into and out of the same stocks and it is 0.0769 (38.45% of overall average correlation) and it is significant at the 99.00% level. The third column of Panel A shows the portion of the correlation that results from institutional investors following other institutional investors and it is 0.1231 (61.55% of overall average correlation) and it significantly differs from zero at the 0.1% level. The t -statistics in the parentheses are calculated from Newey-West standard errors.

Table 1: Descriptive Statistics of Domestic Institutions

This table presents the summary statistics of the sample data from March 2006 to September 2018. All the individual funds under the same institution are aggregated manually by using their portfolio manager institution information in Public Disclosure Platform (KAP). Panel A reports the average number of different institutions for the period and the average number of stocks the institutions hold in their portfolios. At the end of each quarter, each institutional investor's position in each stock is calculated as a fraction of the stock's number of shares outstanding. For each stock and quarter, an institution is defined as a buyer if its ownership in the stock increases and a seller if its ownership decreases. Panel B reports the average number of active institutions per stock for at least 1, 5, 10, 15 and 20 institutions. Panel C reports the average number of stocks traded by at least 1, 5, 10, 15 and 20 institutions and the percentage of BIST 100 stocks among these stocks. Panel D reports the average market capitalization (in billions TRL) of stocks traded for at least 1, 5, 10, 15 and 20 institutions.

Panel A: Number of total institutions & stocks:

	Average all Periods	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
No. of Institutions	46	46	48	46	45	47	49	50	52	46	44	44	43	42
No. of Stocks	207	194	203	192	177	200	213	222	223	212	209	214	216	223

Panel B: Number of institutions for each stock:

	Average all Periods	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
≥ 1 institution	11	11	11	11	10	11	10	11	11	11	11	11	11	12
≥ 5 institutions	15	15	14	14	15	15	15	15	16	16	16	17	15	15
≥ 10 institutions	20	19	19	18	19	18	18	20	20	21	21	21	20	20
≥ 15 institutions	23	22	22	22	22	22	22	23	24	24	24	24	23	23
≥ 20 institutions	26	26	26	24	25	25	25	26	27	27	26	27	26	27

Table 1 (continued).

Panel C: Average number of stocks with:

	Average all Periods	% of BİST 100 Stocks	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
≥ 1 institution	134	62.25	113	125	115	115	122	135	141	143	135	142	147	157	158
≥ 5 institutions	87	80.56	80	86	77	68	82	86	87	87	82	90	87	106	112
≥ 10 institutions	56	91.90	47	53	50	46	52	56	56	59	53	57	57	67	74
≥ 15 institutions	37	97.41	32	33	30	29	32	34	38	39	39	42	44	46	49
≥ 20 institutions	23	99.82	18	17	18	17	18	20	22	26	25	29	29	29	27

Panel D: Average market capitalization (billions TRL) of stocks with:

	Average all Periods	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
≥ 1 institution	3.03	1.70	2.10	1.65	2.11	2.96	2.71	2.97	3.41	3.63	3.55	3.54	4.45	4.67
≥ 5 institutions	4.38	2.31	2.89	2.30	3.20	4.11	3.96	4.51	5.27	5.63	5.29	5.60	6.04	5.88
≥ 10 institutions	6.27	3.45	4.25	3.30	4.48	5.95	5.46	6.32	7.23	8.10	7.77	7.84	8.97	8.34
≥ 15 institutions	8.49	4.34	5.65	4.72	6.43	8.69	8.11	8.51	9.66	10.51	9.94	9.77	12.04	11.94
≥ 20 institutions	11.87	6.72	8.19	5.63	8.48	13.62	11.71	12.00	13.07	14.54	13.02	13.14	17.25	16.88

Table 2: Herding tests for institutions increasing their holdings

Each domestic institution's holdings for each stock is computed as a fraction of the stock's total number of shares outstanding at the end of each quarter for the period of March 2006 and September 2018. A domestic institution is defined as a buyer for each stock and quarter, if its stock holdings as a fraction of total number of shares outstanding increases and a seller if it decreases compared to the previous quarter. The fraction of institutions that increase their holdings to the total number of active institutions is computed for each stock in all the quarters. This fraction is normalized for each stock and quarter. Then, total of 49 cross-sectional regressions are estimated. The independent variable of the cross-sectional regressions is the lag domestic institutional demand and the dependent variable is the current quarter's domestic institutional demand. The estimated regression coefficients are interpreted as cross-sectional correlations because of using one independent variable and normalization of the data. The time-series averages of the 49 cross-sectional regressions' coefficients are shown in the first column of the table. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. The averages of the cross-sectional correlations are decomposed into institutions following their own trades and institutions following others' trades parts and reported in the second and third columns respectively. The fourth column reports the time-series average of R^2 computed from the 49 cross-sectional regressions. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$			
Average coefficient (β)	Partitioned slope coefficient		Average R ²
	Institutions following their own trades	Institutions following others' trades	
Panel A: Stocks with ≥ 1 institution			
0.2000 (9.38) ^{***}	0.0769 (2.73) ^{**}	0.1231 (8.57) ^{***}	5.29%
Panel B: Stocks with ≥ 5 institutions			
-0.0267 (-1.43)	-0.0707 (-6.68) ^{***}	0.0440 (3.09) ^{**}	1.41%
Panel C: Stocks with ≥ 10 institutions			
-0.0536 (-2.11) [*]	-0.0704 (-7.98) ^{***}	0.0169 (0.83)	3.02%
Panel D: Stocks with ≥ 15 institutions			
-0.0696 (-2.41) [*]	-0.0694 (-8.88) ^{***}	-0.0002 (-0.01)	3.80%
Panel E: Stocks with ≥ 20 institutions			
-0.1417 (-3.92) ^{***}	-0.0825 (-9.17) ^{***}	-0.0592 (-2.00)	7.46%

As proposed in Bali *et al.* [148], the number of lags is determined by using $4(T/100)^a$, where T is the number of periods in the time-series, $a = 2/9$ when using the Bartlett kernel, and $a = 4/25$ when using the quadratic spectral kernel to calculate the autocorrelation and heteroscedasticity adjusted standard errors. The number of lags to use in calculating Newey-West standard errors is determined to be 4 because the number of

periods in our analysis is 49. The results reveal that domestic institutions follow themselves and other institutions into and out of the same stocks and herding behavior exists among domestic institutions in BIST.

Since, my data includes stocks with all institutions, my results might be affected by stocks with relatively few institutions. To check for this effect, I repeat the analysis for stocks that have at least five institutions. Panel B of Table 2 shows that overall cross-sectional correlation decreases to -0.0267 and becomes insignificant. However, the institutions following their own trades component is -0.0707 and it is significant at the 0.1% level. This means that institutions are selling (buying) the stocks that they bought (sold) in the previous quarter. The herding measure of the cross-sectional correlation of institutions following others coefficient decreases to 0.0440 and it is significant at the 99.00% level. The evidence of herding weakens, but it persists when the number of active institutions is increased.

The analysis is repeated for at least 10, 15 and 20 institutions and the negativity in the average cross-sectional correlation increases. The herding measure of institutions following others becomes insignificant as the number of active institutions increases. For stocks with more active institutions, there is no evidence of herding in the data. The average coefficient of institutions following others for stocks with at least 20 institutions is -0.0592. The sign and the level indicate a possible contrarian behavior among institutional investors, but the estimation is not significant. The coefficients of institutions following themselves remain negative and significant.

These results indicate that herding among domestic institutions is mainly driven by stocks that are traded by few institutions. The negative correlations of institutions following themselves are also found by Hung *et al.* [116] for the Taiwanese stock market

and by Economou *et al.* [120] for the Bulgarian stock market. This negative coefficient of institutions following themselves may indicate that holding period of institutions are very short. Figure 4 shows the average holding days of domestic investors in BIST. The data in the figure includes individual investors also. However, Gavrilidis *et al.* [142] found a negative relation for the coefficient of institutions following their own trades term from daily changes of stock holdings of the Turkish mutual funds by employing the same methodology (-0.0629 for stocks with at least four active institutions). The evidence of a negative coefficient in a daily study, weakens short-term holding period hypothesis for domestic institutions, because it means that institutions are selling (buying) the stocks today that they bought (sold) yesterday. Sias [1] argues that the coefficient of following others term increases much faster than the coefficient of following themselves terms in the decomposition as the number of institutions increases. There are $N_{k,t}$ following their own trades terms, but $N_{k,t}N_{k,t-1}$ following other institutions term in Equation (35). If an institution trades in only one time period, then that institutions will not contribute to following their own trades term, but will contribute to the herding term. So as the number of institutions increase, the following their own trades term declines and following others (herding) term increases. The negative coefficients for institutions following themselves in daily frequency implies that the number of stocks traded actively decreases as the number of institutions increases.

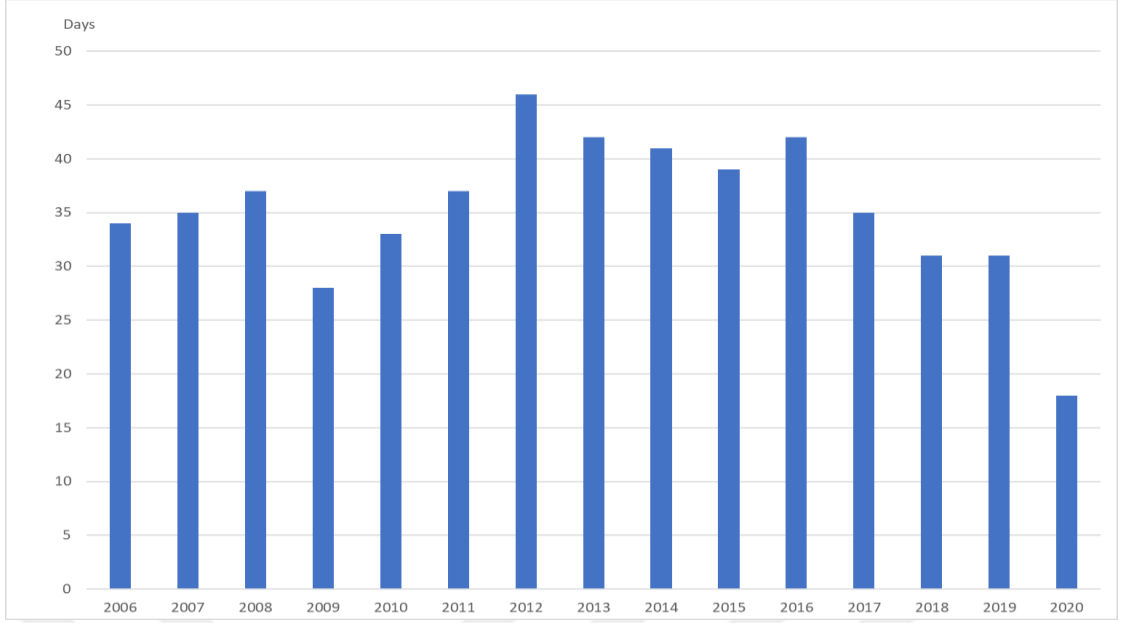


Figure 4: Stock Holding Period of Domestic Investors

This figure presents the average stock holding period (in days) of domestic investors for the period of 2006-2020. (Source: Turkish Capital Markets Association)

3.3 Herding with LSV (1992) Measure

The results in the previous section indicate that the herding behavior of domestic institutional investors is driven by trading in stocks with few institutions. In this section Lakonishok *et al.* [23]’s methodology is applied to the same data to evaluate differences with Sias [1]’s methodology. Kremer & Nautz [102] argue that LSV [23]’s measure is a static measure that detects contemporaneous buying or selling within the same time period. However, Sias [1]’s measure is a dynamic measure that analyze whether buying and selling tendency of investors persists over time. LSV [23] measure herding as the average tendency of a subgroup of investors to buy (sell) an individual stock within the pre-defined time period. The measure for stock k in quarter t is defined as:

$$H_{k,t} = |Raw\Delta_{k,t} - \overline{Raw\Delta_t}| - AF_{k,t} \quad (36)$$

where $Raw\Delta_{k,t}$, the raw fraction of institutions buying is calculated as in Equation (32) and $\overline{Raw\Delta_t}$ is the cross-sectional average raw fraction of institutions buying in quarter t . $AF_{k,t}$, the adjustment factor corrects for herding tendency occurring by chance. $AF_{k,t}$ is calculated for each firm-quarter for at least 1,5,10,15 and 20 institutional investors by assuming the number of institutional investors buying stock k in quarter t follows a binomial distribution with probability $\overline{Raw\Delta_t}$.

The results for stocks with at least 1, 5, 10, 15 and 20 institutions are shown in Table 3. The LSV measure for all actively trading funds is close to zero, but significant at the 99.99% level. The measure for at least 5 institutions increases to 0.0349 and it means that, if 100 funds are trading a given stock in a given quarter, then 3.5 more funds trade on the same side of the market than would be expected if all institutions trade independently. The average level of herding is lower than the findings of the previous works for emerging markets that use the same methodology. Voronkova & Bohl [114] analyze herding behavior among Polish pension funds for the period 1999 to 2002 by using yearly stock ownership data and computes the LSV [23] measure of 22.6%. This high finding is attributed to the highly regulated and concentrated structure of the Polish pension fund system. Patro & Kanagaraj [149] estimate 13.6% for stocks traded by the Indian equity funds for the period of June 2009 to June 2011 on a quarterly basis. Somuncu & Karan [138] analyze the herding behavior of both domestic and foreign institutional investors in BİST for the 2001-2004 period by using LSV [23] measure on a monthly basis. The herding measure is estimated 35.72% for foreign investors and 10.34% for domestic investors. The higher estimates in this study compared to my findings can be attributed to the one of the biggest financial crises of the Turkish economy during that period. The institutional investors may herd due to high informational asymmetries during a crises period and this informational asymmetry is higher for foreign

institutions. Durukan *et al.* [139] investigate the herding behavior of foreign investors between January 2006 and December 2015 on a monthly basis. The average LSV [23] herding measure for the whole period is 3.60%. Evrim *et al.* [140] investigate the herding behavior of 18 equity mutual funds in Turkey for the period from March 2014 to April 2017. LSV [23]'s measure is employed for monthly holdings of these mutual funds. The average herding for the period is estimated 2.001%. The findings of the last two studies that cover my sample period are close to my results. The herding level increases as the number of institutions increases, which is in line with the findings of Lakonishok *et al.* [23] and Sias [1]. The time-series average herding level for 10,15 and 20 or more institutional investors are 0.0434, 0.0466 and 0.0511 respectively. The contrast in the findings of the two methodologies can be attributed to the dynamic structure and the importance of the standard deviations, the number of institutional investors and the number of stocks in Sias [1]'s methodology.

Table 3: Tests for herding-LSV (1992) measure

This table presents the mean and median values of the LSV herding measures for stock quarters where there are at least 1, 5, 10, 15 and 20 active institutions. A domestic institution is defined as a buyer for each stock and quarter, if its stock holdings as a fraction of total number of shares outstanding increases and a seller if it decreases compared to the previous quarter. The fraction of institutions that increase their holdings to the total number of active institutions is computed for each stock in all the quarters. Then the cross-sectional average of the raw fraction of domestic institutions increasing their holdings is computed for each quarter. $AF_{k,t}$ is the adjustment factor that controls for the fact that even in the case of no herding $|Raw\Delta_{k,t} - \overline{Raw\Delta_t}|$ can be greater than zero by chance. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

$$H_{k,t} = |Raw\Delta_{k,t} - \overline{Raw\Delta_t}| - AF_{k,t}$$

Number of Institutions	Mean	Median
≥ 1 institution	0.0082 (5.81)***	0.0079
≥ 5 institutions	0.0349 (16.43)***	0.0360
≥ 10 institutions	0.0434 (18.18)***	0.0428
≥ 15 institutions	0.0466 (14.89)***	0.0452
≥ 20 institutions	0.0511 (13.64)***	0.0498

3.4 Habit Investing

Institutional investors may herd in the markets because they may favor stocks with specific characteristics ([51]). Sias [1] argues a special case of characteristic herding as the habit investing in which institutional investors follow each other into and out of the same stocks because they favor stocks with similar characteristics and this may cause them to hold similar portfolios. Institutions allocate their portfolios by assigning weights to individual stocks. If investors favor stocks with certain characteristics, then they will buy the same stocks when there is a net inflow to the fund and they will sell the same stocks when there is an outflow from the fund to keep the weight of the stock in the portfolio constant. If there is a positive time-series correlation in the portfolios' net flows, then institutional investors will follow themselves into the same stocks when there are inflows to the fund over adjacent quarters. When there are outflows from the funds over adjacent quarters, then the institutional investors will follow themselves out of the same stocks. These buy and sell activities of institutional investors to keep the pre-determined weights unchanged can be interpreted as institutions following themselves. Also, if a group of institutional investors favor the same stocks with certain characteristics and flows to these group of investors' funds exhibit positive time-series and cross-sectional correlations, then these institutional investors may engage in herding behavior. Since they will buy the same stocks when there are inflows to the funds and sell the same stocks when there are outflows from the funds over adjacent quarters, this will create a herding behavior in terms of institutions following each other. For example, if investors' funds are flowing into automobile funds, these funds will be buyers of Ford Otosan. If these mutual funds buy additional shares of Ford Otosan in proportion to their current holdings, the funds' Ford Otosan weights in their portfolios will not change. The changes in Ford

Otosan holdings of the same funds will be treated as an increase in the number of institutions buying in Equation (32), but considering the change in weight will control for fund net flows and correct the herding measurement. Coval & Stafford [150] show that mutual funds buy more of the stocks that they already hold when there is a cash inflow from investors. Similarly, mutual funds have to sell their holdings when there is a cash outflow from the funds. Aydoğan *et al.* [151] find evidence of high persistence in Turkish stock mutual fund flows with stock returns. I examine the correlation between the fraction of institutions increasing their portfolio weights over adjacent quarters to investigate whether habit investing explains herding behavior. If institutional investors follow themselves and each other into and out of the same stocks as a result of habit investing, then portfolio weights should be independent over adjacent quarters. Alternatively, if institutional investors follow themselves and each other into the same stocks for reasons other than time-series and cross-sectional correlations in net flows, then the fraction of institutions increasing portfolio weights will be positively correlated over adjacent quarters.

For each quarter t and institutional investor n , I calculate the portfolio weights ($V_{n,k,t}$) for each stock k by multiplying the adjusted price with the number of stocks held in the investor's portfolio. I compare the current quarter's weight with the previous quarter's weight. However, I use the "return-adjusted" portfolio weights rather than the changes in raw portfolio weights in calculating the previous quarter's weights to eliminate return-induced noise from the analysis. $R_{k,t}$ is the return for stock k over quarter t . By multiplying $V_{n,k,t-1}$ with $1 + R_{k,t}$, I find the theoretical weight at the end of the quarter if the institutional investor did not rebalance his portfolio. Institutional investor n is classified as a buyer (seller) if his end of the quarter portfolio weight is greater (smaller) than his previous quarter's return-adjusted portfolio weight.

$$\frac{V_{n,k,t}}{\sum_{k=1}^K V_{n,k,t}} > \frac{V_{n,k,t-1}(1 + R_{k,t})}{\sum_{k=1}^K V_{n,k,t-1}(1 + R_{k,t})} \quad (37)$$

Then, I compute the number of institutions that increase their return-adjusted portfolio weight as a fraction of the institutions that increase or decrease their return-adjusted portfolio weight for the stock and define it as the raw fraction of institutions increasing their stock k return-adjusted portfolio weights in quarter t:

$$\begin{aligned} RawRAPW\Delta_{k,t} = & \\ & (No. of institutions with increased return_adjusted weight_{k,t}) / \\ & (No. of institutions with increased return - adjusted weight_{k,t} \\ & + No. of institutions with decreased return - adjusted weight_{k,t}) \end{aligned} \quad (38)$$

Next, I standardize $RawRAPW\Delta_{k,t}$ by subtracting the cross-sectional average (across K stocks) and dividing with the cross-sectional standard deviation (across K stocks):

$$\Delta_{k,t} = \frac{RawRAPW\Delta_{k,t} - \overline{RawRAPW\Delta_t}}{\sigma(RawRAPW\Delta_{k,t})} \quad (39)$$

I estimate cross-sectional regressions of the standardized fraction of institutions that increase their return-adjusted portfolio weights on the lagged standardized fraction of institutions that increase their return-adjusted portfolio weights as in Equation (34) and then decompose the slope coefficient β_t into institutions following themselves and institutions following others as in Equation (35).

Panel A of Table 4 shows the time-series average correlation of 49 cross-sectional regressions and decomposition of the average correlation into institutions following themselves and following others components for all actively trading institutions. The

average correlation between the fraction of institutions increasing their return-adjusted portfolio weights in the current quarter and the last quarter is 0.1982 and it is significant at the 99.99% level. This estimation is very close to average correlation coefficient in Panel A of Table 2. The average correlation attributed to institutions following themselves is 0.0608 and significant at the 99.00% level. A slight decrease in this coefficient relative to Panel A in Table 2 means that part of the correlation is coming from institutions trading activities to rebalance the weights of the stocks in their portfolios. The average correlation of institutions following others slightly increases to 0.1374 and it is significant at the 99.99% level. These results do not provide evidence for the hypothesis that institutional herding is the result of habit investing.

In order to control whether the results are driven by stocks with few institutions, the analysis is repeated for stocks with minimum 5 institutions or more. Panel B of Table 4 shows the results. The cross-sectional correlation between institutional demand this quarter and last quarter averages -0.0268 and it is insignificant. However, the portion of correlation that results from institutional investors following themselves into and out of the same stocks is -0.0658 and significant at the 99.99% level. The portion of the correlation that results from institutions following others decreases to 0.0390, but it is significant at the 95.00% level. The herding behavior exists, but it weakens as in the previous section. Panel C, D and E show the results for stocks with at least 10,15, and 20 institutions respectively. Again, the evidence of herding disappears as we increase the number of institutions in the analysis. The coefficient of lagged institutional demand becomes more negative and it is mainly driven by the negative coefficient of institutions following themselves. Since the results are in line with the results in Table 2, the herding behavior of domestic institutional investors is caused by reasons other than correlation in

the net flows to the funds and the hypothesis of herding driven by habit investing is not accepted.

Table 4: Herding tests for institutions increasing their return-adjusted weights

The portfolio weights for each stock is computed by multiplying number of stocks held in the institution's portfolio with the adjusted price between March 2006 and September 2018. The return for each stock is calculated for each quarter. The current quarter's weight is compared with the previous quarter's return-adjusted weight for each stock. Institution is classified as a buyer (seller) if its end of the quarter weight of the stock in the portfolio is greater (smaller) than his previous quarter's return-adjusted stock weight. Then, the number of institutions that increase their return-adjusted portfolio weight as a fraction of the total institutions that change their return-adjusted portfolio weight for the stock is calculated. This fraction is normalized for each stock and quarter. 49 cross-sectional regressions are estimated by using the lag standardized fraction of institutions that increase their return-adjusted stock weights as the independent variable and the standardized fraction of institutions that increase their return-adjusted portfolio weights in the current quarter as the dependent variable. The estimated regression coefficients are interpreted as cross-sectional correlations because of using one independent variable and normalization of the data. The time-series averages of the 49 cross-sectional regressions' coefficients are shown in the first column of the table. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. The averages of the cross-sectional correlations are decomposed into institutions following their trades and institutions following others' trades parts and reported in the second and third columns respectively. The fourth column reports the time-series average of R^2 computed from the 49 cross-sectional regressions. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$			
Partitioned slope coefficient			
Average coefficient (β)	Institutions following their own trades	Institutions following others' trades	Average R^2
Panel A: Stocks with ≥ 1 institution			
0.1982 (11.01)***	0.0608 (3.12)**	0.1374 (11.49)***	5.48%
Panel B: Stocks with $\geq$ institutions			
-0.0268 (-1.24)	-0.0658 (-7.01)***	0.0390 (2.32)*	2.32%
Panel C: Stocks with ≥ 10 institutions			
-0.0476 (-1.96)	-0.0607 (-9.73)***	0.0131 (0.60)	3.06%
Panel D: Stocks with ≥ 15 institutions			
-0.0625 (-2.28)*	-0.0594 (-10.71)***	-0.0031 (-0.12)	4.00%
Panel E: Stocks with ≥ 20 institutions			
-0.1017 (-3.44)**	-0.0688 (-11.51)***	-0.0330 (-1.14)	5.23%

3.5 Momentum Trading

Momentum trading is a well-documented strategy in financial markets and institutional investors are attracted to stocks with higher lagged returns and sell the stocks that have low returns in the past. If a group of institutional investors implements momentum strategies in their trading, then buying stocks with higher lagged returns and selling stocks with poor lagged returns can be interpreted as evidence of herding behavior in the market. The evidence of herding for stocks with relatively few institutions in the previous sections above can be affected by institutions' momentum trading strategies.

To control for momentum trading, lagged stock return is added to the Equation (34) as a standardized independent variable:

$$\Delta_{k,t} = \beta_{1,t}\Delta_{k,t-1} + \beta_{2,t}R_{k,t-1} + \varepsilon_{k,t} \quad (40)$$

where $R_{k,t-1}$ is the lagged quarterly standardized return of stock k. First for each quarter arithmetic return of stock k is calculated by using adjusted prices for dividends and stock splits:

$$r_{k,t} = \frac{P_{k,t}}{P_{k,t-1}} - 1 \quad (41)$$

and then it is standardized as:

$$R_{k,t} = \frac{r_{k,t} - \bar{r}_t}{\sigma(r_{k,t})} \quad (42)$$

where $\bar{r}_t$ is the cross-sectional average stock return in quarter t and $\sigma(r_{k,t})$ is the cross-sectional standard deviation of the stock returns in quarter t.

The average coefficients from the 49 cross-sectional regressions and associated t-statistics calculated from Newey-West standard errors are presented in Table 5. The results for stocks with at least one institution in Panel A show that domestic institutional investors engage in momentum trading. The average coefficient of lagged standardized returns is 0.0605 and it is significant at the 99.99% level. The result is close to the 0.0691 level found in Sias [1] and it means that one standard deviation increase in the previous quarter's return lead to a 6.05% standard deviation increase in institutional demand this quarter. The average coefficient of the lagged fraction of institutions buying is estimated as 0.2028. It is slightly higher than the estimation in Panel A of Table 2.

Table 5: Tests of momentum trading for institutions increasing their holdings

Each domestic institution's holdings for each stock is computed as a fraction of the stock's total number of shares outstanding at the end of each quarter for the period of March 2006 and September 2018. A domestic institution is defined as a buyer for each stock and quarter, if its stock holdings as a fraction of total number of shares outstanding increases and a seller if it decreases compared to the previous quarter. The fraction of institutions that increase their holdings to the total number of active institutions is computed for each stock in all the quarters. This fraction is normalized for each stock and quarter. The lagged quarterly stock returns are calculated and standardized. Then 49 quarterly cross-sectional regressions are estimated by using lagged institutional demand and lagged quarterly stock returns as independent variables, and institutional demand in the current quarter as the dependent variable. The estimated regression coefficients are interpreted as cross-sectional correlations because of the normalization of the data. The time-series averages of the 49 cross-sectional regressions' coefficients are shown in the first and second columns of the table. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. The third column reports the time-series average of R^2 computed from the 49 cross-sectional regressions. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

$\Delta_{k,t} = \beta_{1,t}\Delta_{k,t-1} + \beta_{2,t}R_{k,t-1} + \varepsilon_{k,t}$		
Average coefficient associated with lag institutional demand (β_1)	Average coefficient associated with lag return (β_2)	Average R^2
Panel A: Stocks with ≥ 1 institution		
0.2028 (9.03)***	0.0605 (3.62)***	6.65%
Panel B: Stocks with ≥ 5 institutions		
-0.0199 (-1.07)	0.0437 (1.66)*	3.73%
Panel C: Stocks with ≥ 10 institutions		
-0.0522 (-2.09)*	0.0051 (0.15)	6.04%
Panel D: Stocks with ≥ 15 institutions		
-0.0765 (-2.49)**	-0.0271 (-0.77)	8.03%
Panel E: Stocks with ≥ 20 institutions		
-0.1609 (-3.62)***	-0.0661 (-1.57)	14.48%

Thus, adding lagged standardized return to the model has no major effect on our herding estimation, but it improves the R^2 of the model. The lagged institutional demand has more explanatory power than the lagged returns in the model. Panel B shows the results for stocks with 5 or more institutions. The average standardized lagged returns coefficient decreases to 0.0437 and remains significant at the 95.00% level. The average coefficient of lagged institutional demand is -0.0199 and it is insignificant. The results are again similar to the results shown in Panel B of Table 2. The institutional investors apply momentum trading strategies, but herding behavior is not driven by momentum. Panel C, D and E show the results for stocks with at least 10,15, and 20 investors. The momentum effect becomes insignificant as the number of active institutions increase. The average coefficient for lagged fraction of institutions buying remains similar to the results presented in Table 2.

The analysis is repeated for the standardized fraction of institutions increasing return-adjusted portfolio weights. The results are presented in Table 6. The institutional investors implement momentum strategies in stocks with at least 1 and 5 institutions, but momentum trading is not the primary reason for herding behavior. The lagged institutional demand is more important for the herding behavior. As the number of active institutions increases, momentum effect disappears from the estimation. The average coefficients of lagged standardized return-adjusted buying of institutions in the regression are similar to the results shown in Table 2. The domestic institutional investors implement momentum strategies for small size stocks with relatively few institutions, but these strategies do not cause the herding behavior.

Table 6: Tests of momentum trading for institutions increasing their return-adjusted weights

The portfolio weights for each stock is computed by multiplying number of stocks held in the institutional investor's portfolio with the adjusted price between March 2006 and September 2018. The return for each stock is calculated for each quarter. The current quarter's weight is compared with the previous quarter's return-adjusted weight for each stock. Institutional investor is classified as a buyer (seller) if his end of the quarter weight of the stock in the portfolio is greater (smaller) than his previous quarter's return-adjusted stock weight. Then, the number of institutional investors that increase their return-adjusted portfolio weight as a fraction of the total institutional investors that change their return-adjusted portfolio weight for the stock is calculated. This fraction is normalized for each stock and quarter. The lag quarterly stock returns are calculated and standardized. 49 cross-sectional regressions are estimated by using the lag standardized fraction of institutions that increase their return-adjusted stock weights and lag quarterly stock returns as the independent variables and the standardized fraction of institutions that increase their return-adjusted portfolio weights in the current quarter as the dependent variable. The estimated regression coefficients are interpreted as cross-sectional correlations because of the normalization of the data. The time-series averages of the 49 cross-sectional regressions' coefficients are shown in the first and second columns of the table. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. The third column reports the time-series average of R^2 computed from the 49 cross-sectional regressions. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

$\Delta_{k,t} = \beta_{1,t}\Delta_{k,t-1} + \beta_{2,t}R_{k,t-1} + \varepsilon_{k,t}$		
Average coefficient associated with lag institutional demand (β_1)	Average coefficient associated with lag return (β_2)	Average R^2
Panel A: Stocks with ≥ 1 institution		
0.2002 (7.70)***	0.0661 (3.76)***	6.78%
Panel B: Stocks with ≥ 5 institutions		
-0.0215 (-0.93)	0.0509 (2.41)**	3.94%
Panel C: Stocks with ≥ 10 institutions		
-0.0417 (-1.37)	0.0277 (0.88)	5.99%
Panel D: Stocks with ≥ 15 institutions		
-0.0657 (-2.13)*	-0.0101 (-0.31)	7.32%
Panel E: Stocks with ≥ 20 institutions		
-0.1059 (-2.87)***	-0.0438 (-1.60)	11.64%

3.6 Institutional Demand & Subsequent Stock Returns

A positive relation between institutional demand and returns in the previous and current period is identified in the previous works ([63]; [62]; [1]). Also, a weak positive relation between institutional demand and future returns is found in these works. However, some other works identify the destabilizing effect of institutional demand and herding on stock prices ([122]; [98]). If the herding behavior results from non-informational motives like

reputational concerns, characteristic herding and fads, then there will be a return reversal in the future. Thus, institutional demand will be inversely correlated with future returns. If the herding behavior is driven by information-based motives like informational cascades or investigative herding, then there will be no destabilizing effect of herding in the market. In the case of investigative herding and the information cascades, the subsequent returns for the stocks that institutions heavily bought (sold) will be high (low). To test whether institutional demand has a stabilizing or destabilizing effect on the stock returns, the cross-sectional correlation between the fraction of institutions buying (Equation (32)) and returns of the previous quarter, the current quarter, the following quarter, following six months and following twelve months are examined. Table 7 shows the results of the cross-sectional correlations for stocks with at least 1, 5, 10, 15 and 20 institutional investors. A positive and significant cross-sectional correlation between the fraction of institutions buying and previous quarter return is identified for stocks with at least 1 and 5 institutions. This result is in line with the findings in the momentum trading section above. The positive relation disappears as the number of institutions increases and this is also in line with the findings in the momentum trading section. The averages of cross-sectional correlations between fraction of institutions buying and current quarter returns are significantly negative for all different numbers of institutions. This negative correlation arises mostly from stocks with at least 20 institutions, which is estimated as -29.66%. This means that institutional investors mostly buy the stocks that have negative returns and sell the stocks that have positive returns in the current quarter. The stocks with at least 20 institutions are mostly large-size stocks as shown in Table 1. The institutions act as market stabilizers in these stocks and prevent market participants to deviate stock prices from their fundamental values. The correlations for the following quarter, following six months and following twelve months are close to zero and

insignificant. The herding behavior is detected for stocks with relatively few institutions and correlation between institutional demand and previous quarter returns are positive, which is in line with the previous studies ([62]; [1]). However, the result of a high negative correlation between institutional demand and returns for stocks with at least 20 institutions is different from the result found by Sias [1]. This evidence means that the domestic institutions sell (buy) the stocks that are over-performing (underperforming). The lack of evidence for return reversal in the subsequent periods can be interpreted as information-based herding behavior of informational cascades and investigative herding.

Table 7: Correlations between institutional demand & stock returns

Each domestic institution's holdings for each stock is computed as a fraction of the stock's total number of shares outstanding at the end of each quarter for the period of March 2006 and September 2018. A domestic institution is defined as a buyer for each stock and quarter, if its stock holdings as a fraction of total number of shares outstanding increases and a seller if it decreases compared to the previous quarter. The fraction of institutions that increase their holdings to the total number of active institutions is computed for each stock in all the quarters. The cross-sectional correlations between the fraction of institutions buying in the current quarter and stock returns of the previous quarter, the current quarter, the following quarter, the following six months and the following twelve months are computed. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

Sample	Previous quarter return	Same quarter return	Following quarter return	Following 6-month return	Following 12-month return
≥ 1 institution	0.0413 (2.71)**	-0.0832 (-3.49)**	0.0122 (0.80)	0.0206 (1.37)	0.0216 (1.01)
≥ 5 institutions	0.0697 (3.16)**	-0.1488 (-7.67)***	0.0152 (0.89)	0.0065 (0.35)	0.0058 (0.30)
≥ 10 institutions	0.0330 (1.02)	-0.1947 (-9.68)***	0.0170 (0.78)	0.0087 (0.47)	0.0184 (1.07)
≥ 15 institutions	0.0172 (0.48)	-0.2320 (-12.04)***	0.0010 (0.31)	-0.0094 (-0.41)	0.0083 (0.31)
≥ 20 institutions	0.0057 (0.17)	-0.2966 (-9.99)***	-0.0083 (-0.34)	-0.0136 (-0.53)	0.0084 (0.14)

3.7 Herding by Firm Size

The absence of destabilizing effects of institutional demand on subsequent stock returns in terms of a return reversal supports the hypothesis of herding driven by informational motivations.

Table 8: Herding tests by market capitalization quantile

Each domestic institution's holdings for each stock is computed as a fraction of the stock's total number of shares outstanding at the end of each quarter for the period of March 2006 and September 2018. A domestic institution is defined as a buyer for each stock and quarter, if its stock holdings as a fraction of total number of shares outstanding increases and a seller if it decreases compared to the previous quarter. The fraction of institutions that increase their holdings to the total number of active institutions is computed for each stock in all the quarters. This fraction is normalized for each stock and quarter. Stocks that have at least one active institution are sorted and divided into five size quintiles for each quarter. Then, total of 49 cross-sectional regressions are estimated within each capitalization quintile. The independent variable of the cross-sectional regressions is the lagged domestic institutional demand and the dependent variable is the current quarter's domestic institutional demand. The estimated regression coefficients are interpreted as cross-sectional correlations because of using one independent variable and normalization of the data. The time-series averages of the 49 cross-sectional regressions' coefficients are shown in the first column of the table. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. The averages of the cross-sectional correlations are decomposed into institutions following their own trades and institutions following others' trades parts and reported in the second and third columns respectively. The fourth column reports the time-series average of R^2 computed from the 49 cross-sectional regressions. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

Capitalization quintile	Average coefficient (β)	Partitioned slope coefficient		Average R^2
		Institutions following their own trades	Institutions following others' trades	
Small firms	0.2291 (11.45)***	0.0932 (4.78)***	0.1360 (6.99)***	7.17%
Quintile 2	0.1232 (3.77)***	0.0027 (0.14)	0.1205 (4.09)***	6.65%
Quintile 3	0.0395 (0.76)	-0.0270 (-1.55)	0.0666 (1.45)	13.20%
Quintile 4	-0.0271 (-0.53)	-0.0615 (-3.12)**	0.0344 (0.74)	12.78%
Large firms	-0.2956 (-4.82)***	-0.1076 (-6.68)***	-0.1880 (-3.06)**	26.77%

The private information in small-capitalization stocks that the investors received, is noisier. Information cascades are more likely seen among small-capitalization stocks because investors will disregard their own private information and will follow the others ([62]). In large-capitalization stocks the investigative herding will be more likely to form

because cross-sectionally correlated signals are more likely to occur in these stocks ([1]). These stocks are followed by many analysts and the media coverage is higher in these stocks. In this section the data is analyzed by size capitalization quantiles. The data is sorted in each quarter by market-capitalization and it is divided into five quantiles. Then, the cross-sectional correlation between the fraction of institutions buying in the current quarter and the fraction of institutions buying in the previous quarter is estimated as in Equation (34) for each quintile. The first row of Table 8 presents the results for the lowest capitalization quantile. The cross-sectional correlation is estimated as 0.2291 and it is significant at the 99.99% level. 0.0932 of this correlation results from institutions following themselves, and 0.1360 of the correlation arises from institutions following other institutions. This means that there is a tendency of herding among institutions in the lowest market-capitalization quantile and it is significant at the 99.99% level. The cross-sectional correlation of institutions following other institutions coefficient is 0.1205 and it is significant at the 99.99% level for the second quantile. These estimations show that herding behavior among domestic institutional investors exists in relatively small-capitalization stocks. There is no significant correlation for the third and the fourth quantiles. For the largest capitalization stocks, the cross-sectional correlation is estimated as -0.2956 which is significant at 99.99%. -0.1076 of this correlation arises from institutions following themselves and -0.1880 of the correlation arises from institutions following other institutions. Instead of herding behavior in large-capitalization stocks, the institutions implement contrarian strategies, which means they are selling (buying) the stocks in the current quarter that other institutions bought (sold) in the previous quarter. The domestic institutional investors feel confident in their private information in the large-capitalization stocks and act like a market-maker in these stocks. Wylie [65] finds evidence of contrarian trading strategies of the UK mutual funds and explains it by the

dominance of mutual funds in the stock market. The evidence of herding in small-capitalization stocks and contrarian trading in large-capitalization stocks support the hypothesis that the herding behavior of domestic institutions in BİST is the result of herding due to information cascades.

3.8 Conclusion

This chapter investigates herding behavior among domestic institutional investors in Borsa İstanbul over the sample period between March 2006 and September 2018. This is the first study that examines in detail the domestic institutional investor herding in the Turkish stocks by using Sias [1]’s methodology. First, I estimate the cross-sectional correlation between standardized institutional demand in the current quarter and in the previous quarter for different number of active institutions and decompose the cross-sectional correlation into institutions following their own trades and following others’ trades parts. The estimation results reveal that herding behavior exists, but it is mainly driven by stocks traded by relatively few institutions. Second, I investigate whether herding behavior is caused by cross-sectional and time-series correlations in the flows to funds, but fail to find any evidence of habit investing. There exists a momentum trading effect mainly driven by stocks with relatively few institutions, but the results suggest that the lagged institutional demand is more important than the lagged return on the current period’s institutional demand. There is no relation between institutional demand and future returns which indicates that the destabilizing effects of institutional demand do not exist and herding behavior is driven by informational motives. I find a negative relationship between institutional demand and the current quarter’s returns for stocks with at least 20 active institutions. Finally, sorting stocks by market capitalization reveal that domestic institutional investors herd in small-capitalization stocks and this behavior is

caused by ignoring the private own information and following the prior trades of others. In large-capitalization stocks, the domestic institutional investors implement negative feedback trading strategies instead of herding.



CHAPTER IV

HERDING OF FOREIGN INSTITUTIONAL INVESTORS IN BORSA İSTANBUL

4.1 Introduction

The foreign investors have gained importance in emerging markets after the liberalization of capital accounts in these countries and there has been a massive amount of capital inflow to these countries. Turkey is one of the emerging markets, where foreign investors have significant presence. Figure 5 presents the share of foreign investors in transaction volume and total holdings in BİST for the period of 2006 to 2020. The average foreign holdings account to 64.40% of all stocks and 21.65% of the transaction volume over this period is executed by foreign institutional investors.

The analysis of institutional herding in Borsa İstanbul (BİST) will be incomplete without taking into consideration the foreign institutional investors. There are relatively few studies that compare the herding behavior of both domestic and foreign institutions by using the stock holdings data. Bowe & Domuta [113] find a higher herding tendency of foreign institutions in Indonesia. Somuncu & Karan [138] analyze the herding behavior of both domestic and foreign institutions in Turkey for the period of 2001-2004. The authors find a higher herding level for foreign institutional investors compared to local institutions. This study is a contribution to the literature in institutional herding by using the Sias [1]’s herding measure and by adding foreign institutional investors in the analysis.

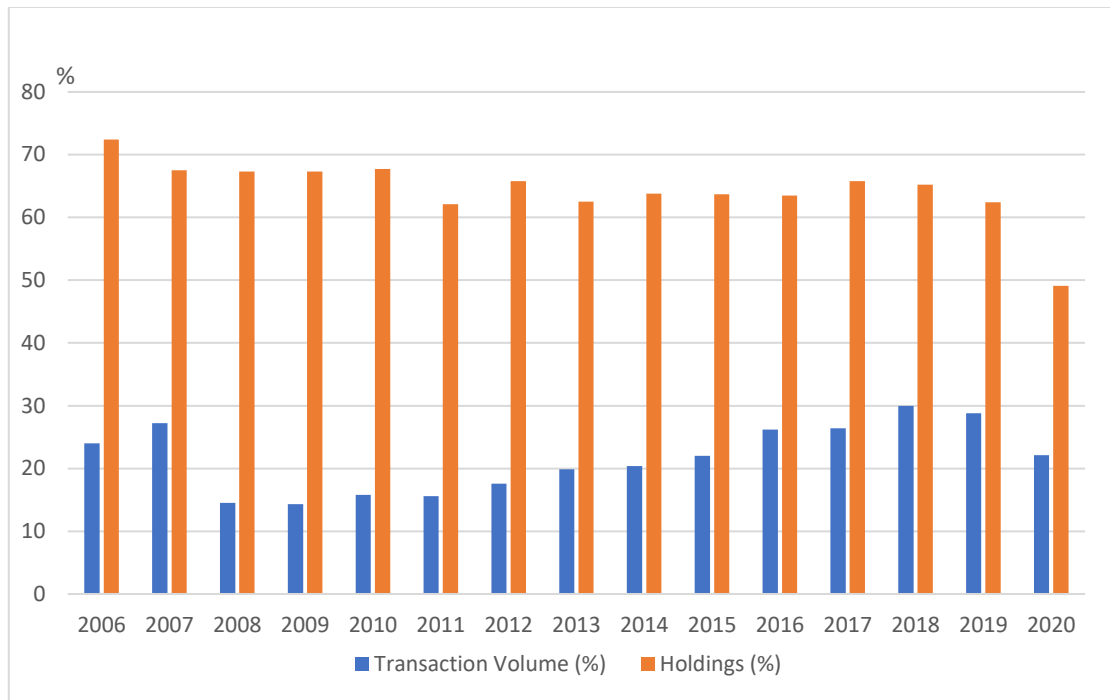


Figure 5: Yearly Transaction Volume & Holdings of Foreign Institutional Funds

This figure shows the share of foreign institutional investors in total transaction volume and in the holdings for the period of 2006-2020. (Source: Turkish Capital Markets Association)

It is argued that there is a high tendency to herd among foreign institutional investors because their trades are highly correlated ([99]). It is also argued that foreign investors follow destabilizing strategies that make stock prices overreact and deviate from fundamentals ([152]). The herding behavior of foreign institutional investors and their positive feedback trading strategies are well-documented in the previous studies. The foreign institutional herding and positive feedback trading strategies are found for Korea ([99]), Japan ([125]), India ([112]), Indonesia ([113]), Taiwan ([115]; [117]) and Turkey ([138]).

The results of this study show that lagged foreign institutional demand is related to the current foreign institutional demand and this relation does not disappear as we increase the number of institutions for each stock. The partition of the coefficient into institution following themselves and following others parts also differs from domestic

institutions. The coefficient of the foreign institutions following themselves decreases as we consider stocks with more institutions. On the other hand, the coefficient of the foreign institutions following others gets stronger as the number of institutions is increased. There is an evidence of herding for foreign institutions, which is higher than the domestic institutions and it gets stronger for stocks that are traded by more institutions. The foreign investors' herding behavior is not driven by their attraction to stocks with specific characteristics. The foreign institutional investors implement momentum strategies more than the domestic institutions, but the herding behavior is not driven by these momentum strategies. The correlations between the foreign institutional demand and stock returns of the previous, current and future quarters are also examined. There is a positive relation between current institutional demand and past quarter stock returns. Also, the positive relation is identified between the current institutional demand and the stock returns of the current quarter. There is no evidence found for destabilizing effects of the current foreign institutional demand on the future stock returns. The absence of any return reversal in the future periods eliminates the case for non-informational herding explanations. The analysis for stocks with different market capitalizations shows that foreign institutions herd in small-capitalization and large-capitalization stocks.

The structure of the paper is as follows. Section 2 describes the foreign institutional data. Section 3 presents the empirical findings of herding analysis by using Sias [1] measure. Sections 4 and 5 present the empirical findings for habit investing and momentum trading. Section 6 investigates the relation between institutional demand and returns. Section 7 presents the results of the herding tests for different size quantiles. Section 8 shows the results of returns comparison for domestic and foreign institutions. Section 9 concludes.

4.2 Foreign Institutional Data

The data of foreign institutional investors' stock holdings is gathered from EquityRT module of Rasyonet. The data is on quarterly basis and covers the period of Q1-2006 to Q3-2018. I use the equity holdings of asset managers' data instead of holdings data of individual funds because the same managers can manage different funds and their trading activities may create an overestimation in the herding measure.

The descriptive statistics of the data are presented in Table 9. Panel A shows the number of asset managers and stock holdings for the sample period. There are on average 642 different foreign asset managers in the data. This is very high compared to the average number of domestic institutional investors for the period. The foreign institutional investors hold on average 182 different stocks in their portfolios for the period. The foreign institutional investors are interested in lower number of stocks compared to domestic institutional investors (average is 207 for domestic investors).

Panel B of Table 9 shows the average number of active foreign institutions for each stock in the data. For all active institutions, there are on average 30 different foreign asset managers trading a particular stock. As the number of active foreign institutions increases, the average of number of active institutions for each stock also increases and it reaches to 68 for stocks with at least 20 institutions. Panel C of Table 9 shows the average number of securities traded for different number of active institutions. The average number of securities traded by all active foreign institutions is 159 and 71.10% of it consists of BİST 100 stocks. As the number of institutions increases, the number of stocks traded decreases and a higher share of the traded equities consists of BİST 100 stocks, but the share of BİST 100 stocks is lower compared to domestic institutions.

Table 9: Descriptive Statistics of Foreign Institutions

This table presents the summary statistics of our foreign institutional investors' sample data from March 2006 to September 2018. The data is gathered from EquityRT module of Rasyonet. Panel A reports the average number of different institutions for the period and the average number of stocks the institutions hold in their portfolios. At the end of each quarter, each institutional investor's position in each stock is calculated as a fraction of the stock's number of shares outstanding. For each stock and quarter, an institution is defined as a buyer if its ownership in the stock increases and a seller if its ownership decreases. Panel B reports the average number of active institutions per stock for at least 1, 5, 10, 15 and 20 institutions. Panel C reports the average number of stocks traded by at least 1, 5, 10, 15 and 20 institutions and the percentage of BİST 100 stocks among these stocks. Panel D reports the average market capitalization (in billions TRL) of stocks traded for at least 1, 5, 10, 15 and 20 institutions.

Panel A: Number of total institutions & stocks:

	Average all Periods	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
No. of Institutions	642	458	578	624	647	684	679	658	695	692	682	661	658	635
No. of Stocks	182	182	192	175	163	167	182	181	195	191	190	185	179	182

Panel B: Number of asset managers for each stock:

	Average all Periods	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
≥ 1 institution	30	23	24	27	29	32	30	30	34	33	34	31	31	29
≥ 5 institutions	40	30	32	35	40	42	41	41	47	45	44	42	41	38
≥ 10 institutions	51	41	42	43	51	51	50	53	59	59	57	56	52	48
≥ 15 institutions	60	50	50	50	58	60	59	61	68	70	68	66	65	57
≥ 20 institutions	68	53	58	54	65	68	66	69	76	78	77	76	72	66

Table 9 (continued).

Panel C: Average number of stocks with:

	Average all Periods	% of BİST 100 Stocks	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
≥ 1 institution	159	71.10	142	150	138	142	143	161	170	154	168	165	173	176	181
≥ 5 institutions	115	80.78	102	109	104	101	106	117	119	109	117	124	124	127	134
≥ 10 institutions	85	86.19	68	78	81	73	84	91	89	84	85	90	88	95	99
≥ 15 institutions	68	91.45	51	59	66	62	67	72	73	70	69	72	72	70	80
≥ 20 institutions	57	95.46	45	48	58	53	55	61	61	60	59	61	59	62	65

Panel D: Average market capitalization (billions TRL) of stocks with:

	Average all Periods	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
≥ 1 institution	2.64	1.33	1.67	1.67	1.56	2.45	2.58	2.35	3.29	2.95	3.26	3.10	3.80	4.29
≥ 5 institutions	3.45	1.78	2.21	2.14	2.06	3.22	3.33	3.18	4.45	4.01	4.28	4.03	4.85	5.26
≥ 10 institutions	4.47	2.66	3.00	2.64	2.62	3.97	4.08	4.01	5.60	5.27	5.68	5.45	6.37	6.73
≥ 15 institutions	4.78	3.00	2.64	2.62	3.97	4.08	4.01	5.60	5.27	5.68	5.45	6.37	6.73	6.73
≥ 20 institutions	6.27	3.75	4.42	3.71	3.40	5.51	5.82	5.59	7.48	7.11	7.89	7.77	9.06	10.05

The average number of securities traded by at least 20 institutions becomes 57 and 95.46% of them are BIST 100 stocks. There are more stocks traded for each different number of institutions compared to domestic institutional investors. Panel D of Table 9 shows the average market-capitalization of stocks (in billion TL) traded by different number of foreign institutions. The average capitalization is 2.64 billion TL for all active institutions. But the average capitalization increases as the number of active institutions increases. The average market-capitalization of stocks with at least 20 active foreign institutions is 6.27 billion TL for the whole period. The average market-capitalization for different number of foreign institutional investors is lower than the market-capitalization of stocks traded by domestic institutional investors.

4.3 Herding Estimation

The methodology of Sias [1] is repeated for foreign institutional investors by following the steps in Equation (32) to Equation (35). First, at the end of each quarter, each institutional investor's position in each security as a fraction of the security's number of shares outstanding is computed. For each security and quarter, an institutional investor is defined as a buyer if its ownership in the stock increases and a seller if its ownership decreases. For each stock quarter, the fraction of institutional investors trading the security that are buyers to the number of actively trading institutional investors is calculated. All data are standardized by subtracting the mean and dividing by the standard deviation in each quarter. Then, 49 quarterly cross-sectional regressions are estimated by using the foreign institutional demand in the previous quarter as the independent variable, and the foreign institutional demand in the current quarter as the dependent variable. Finally, the estimated coefficients are decomposed into foreign institutions following themselves and following others parts. The time-series average of the estimated

coefficients for all active institutions and the t-statistics calculated by Newey-West standard errors using 4 lags are presented in the first column of Panel A in Table 10. One standard deviation increase (decrease) in standardized lagged fraction of institutional buyers (sellers) leads to 34.59% standard deviation increase (decrease) in standardized fraction of institutional buyers (sellers) in the current quarter. Since the data is standardized, the coefficients are considered as the cross-sectional correlations. The cross-sectional correlation is estimated higher than the coefficient for domestic institutions. The decomposition results reported in the second and third columns of Table 10. Panel A of the table shows that 52.10% ($0.1802/0.3459$) of this correlation arises from institutions following themselves. This estimation includes all active institutions and the foreign investors trade stocks with low market capitalization and liquidity. Since the foreign institutional investors are closely monitored by the other investors, their trading decisions are distributed throughout time for minimizing the impact of their demand on the stock price in small capitalization stocks. The cross-sectional correlation for institutions following others (the real herding measure) is estimated 16.57% and it is significant at 99.99% level. There is an evidence of herding behavior among foreign institutional investors for the sample period and it is stronger than the herding behavior for the domestic institutions in Chapter III. The analysis is repeated for stocks with at least 5, 10, 15 and 20 active institutions to control whether the results are affected by stocks with few active institutions. The results are presented in Panel B, C, D and E of Table 10 respectively. The time-series average of cross-sectional correlation between current institutional demand and lagged institutional demand decreases to 23.02% for stocks with at least 5 institutions. However, this decrease is due to the lower correlation arising from institutions following themselves part. The time-series average of the cross-sectional correlation of the institutions following themselves is estimated as 3.75% and it

is significant at the 99.99% level. The cross-sectional correlation coefficient of institutions following others is estimated 19.27%. The herding behavior of foreign institutional investors gets stronger as the sample is limited to stocks with relatively more institutions. The cross-sectional correlation of institutions following themselves becomes 20.82%, 22.67% and 23.77% for stocks with at least 10,15 and 20 institutions respectively. The foreign institutions have a greater tendency to herd in BIST and this herding tendency is not driven by stocks with few institutions.

Table 10: Herding tests for institutions increasing their holdings (Foreign)

Each foreign institutional investor's holdings for each stock is computed as a fraction of the stocks' total number of shares outstanding at the end of each quarter for the period of March 2006 and September 2018. A foreign institutional investor is defined as a buyer for each stock and quarter, if its stock holdings as a fraction of total number of shares outstanding increases and a seller if it decreases compared to the previous quarter. The fraction of institutions that increase their holdings to the total number of active institutions is computed for each stock in all the quarters. This fraction is normalized for each stock and quarter. Then, total of 49 cross-sectional regressions are estimated. The independent variable of the cross-sectional regressions is the lagged foreign institutional demand and the dependent variable is the current quarter's foreign institutional demand. The estimated regression coefficients are interpreted as cross-sectional correlations because of using one independent variable and normalization of the data. The time-series averages of the 49 cross-sectional regressions' coefficients are shown in the first column of the table. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. The averages of the cross-sectional correlations are decomposed into institutions following their trades and institutions following others' trades parts and reported in the second and third columns respectively. The fourth column reports the time-series average of R^2 computed from the 49 cross-sectional regressions. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$			
	Partitioned slope coefficient		
Average coefficient (β)	Institutions following their own trades	Institutions following others' trades	Average R ²
Panel A: Stocks with ≥ 1 institution			
0.3459 (14.34)***	0.1802 (8.17)***	0.1657 (6.30)***	13.60%
Panel B: Stocks with ≥ 5 institutions			
0.2302 (14.56)***	0.0375 (4.83)***	0.1927 (12.41)***	7.40%
Panel C: Stocks with ≥ 10 institutions			
0.2370 (9.89)***	0.0289 (6.10)***	0.2082 (8.17)***	8.78%
Panel D: Stocks with ≥ 15 institutions			
0.2472 (7.65)***	0.0206 (5.15)***	0.2267 (6.74)***	10.88%
Panel E: Stocks with ≥ 20 institutions			
0.2585 (9.71)***	0.0208 (6.88)***	0.2377 (8.79)***	10.49%

Table 11: Herding tests for institutions increasing their holdings (All)

Each institutional investor's holdings for each stock is computed as a fraction of the stocks' total number of shares outstanding at the end of each quarter for the period of March 2006 and September 2018. An institutional investor is defined as a buyer for each stock and quarter, if its stock holdings as a fraction of total number of shares outstanding increases and a seller if it decreases compared to the previous quarter. The fraction of institutions that increase their holdings to the total number of active institutions is computed for each stock in all the quarters. This fraction is normalized for each stock and quarter. Then, total of 49 cross-sectional regressions are estimated. The independent variable of the cross-sectional regressions is the lagged institutional demand and the dependent variable is the current quarter's institutional demand. The estimated regression coefficients are interpreted as cross-sectional correlations because of using one independent variable and normalization of the data. The time-series averages of the 49 cross-sectional regressions' coefficients are shown in the first column of the table. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. The averages of the cross-sectional correlations are decomposed into institutions following their trades and institutions following others' trades parts and reported in the second and third columns respectively. The fourth column reports the time-series average of R^2 computed from the 49 cross-sectional regressions. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$			
Partitioned slope coefficient			
Average coefficient (β)	Institutions following their own trades	Institutions following others' trades	Average R^2
Panel A: Stocks with ≥ 1 institution			
0.2877 (12.21)***	0.1461 (5.67)***	0.1417 (10.30)***	9.58%
Panel B: Stocks with ≥ 5 institutions			
0.1041 (5.57)***	-0.0130 (-1.36)	0.1171 (7.56)***	2.53%
Panel C: Stocks with ≥ 10 institutions			
0.1429 (6.97)***	-0.0078 (-1.01)	0.1506 (7.19)***	3.96%
Panel D: Stocks with ≥ 15 institutions			
0.1771 (10.38)***	-0.0040 (-0.63)	0.1811 (10.09)***	5.59%
Panel E: Stocks with ≥ 20 institutions			
0.1856 (8.82)***	-0.0059 (-1.35)	0.1915 (9.65)***	6.00%

The same analysis is repeated for both domestic and foreign institutions and the results are presented in Table 11. The time-series average of the correlations between current quarter's institutional demand and the previous quarter's institutional demand is estimated 28.77%. 50.78% (0.1461/0.2877) of this correlation comes from institutions following themselves and 49.22% (0.1417/0.2877) comes from foreign institutions

investors following other foreign institutions. The time-series average of the correlations between current quarter's institutional demand and the previous quarter's institutional demand for stocks with at least 5 active trader decreases to 10.41%. The significant part of this decrease results from the institutions following themselves coefficient which is estimated -0.0130 and it is insignificant. The coefficient of institutions that are following themselves remains negative and insignificant for stocks with at least 10, 15 and 20 institutions. On the other hand, the cross-sectional correlation of institutions following themselves is estimated as 11.71% for stocks with at least 5 institutions in Panel B of Table 11. Panel C, D and E show the results for stocks with at least 10, 15 and 20 institutions. The results show that the real herding measure of institutions following others increase with stocks that have a higher number of institutions.

4.4 Habit investing

The foreign institutional investors may prefer stocks with specific characteristics and hold similar stocks in their portfolios. Then, these investors may have a correlation in their trades because of holding similar portfolios. If there are time-series and cross-sectional correlations in the net flows to the institutional investors, then holding similar portfolios because of characteristics herding may cause them entering into correlated trades. Sias [1] defines this special case of characteristic herding as habit investing. When there is a net inflow to the fund, the manager will buy the same stocks to balance the weight of the stocks in the portfolio. When there is an outflow from the fund, the manager will sell the stocks from the portfolio to protect the weight allocations in the fund. These buy and sell activities to keep the portfolio weights constant may lead to a correlation between the institutional investors' following themselves and following others coefficients. In order

to control for this effect, I define a foreign institution as a buyer (seller) when that institution increases (decreases) his return adjusted weight in a particular stock.

I calculate the standardized fraction of foreign institutional investors that increase return-adjusted stock weights in their portfolios by following the steps in Equations (37) and (38) to test for habit investing. Then, 49 cross-sectional regressions are estimated by using the lagged standardized fraction of institutions that increase their return-adjusted stock weights as the independent variable and the standardized fraction of institutions that increase their return-adjusted portfolio weights in the current quarter as the dependent variable. and decompose the slope coefficient β_t into institutions following themselves and then partition the slope coefficient β_t into institution investors following themselves and following others parts as shown in Equation (35). The first column of Table 12 presents the time-series averages of the 49 cross-sectional regression for the foreign institutional investors. The second and the third column presents the time-series averages of the decomposition into institutions following themselves and following others. The overall results reveal that cross-sectional correlation between the standardized fraction of foreign institutional investors that increase their return-adjusted weights in the current quarter and the standardized fraction of foreign institutional investors that increase their return-adjusted weights in the previous quarter is not caused by habit investing. Panel A in Table 12 presents the results for all active institutions. The estimated cross-sectional regression coefficients are considered as correlations due to the normalization. The time-series average of the 49 cross-sectional correlations is 39.38%. 64.20% (0.2528/0.3938) of this correlation results from institutions following themselves, and 35.80% (0.1410/0.3938) of the correlation results from institutions following others. The habit investing is not an explanatory factor for foreign institutional herding.

Table 12: Herding tests for institutions increasing their return-adjusted weights (Foreign)

The portfolio weights for each stock is computed by multiplying number of stocks held in the institutional investor's portfolio with the adjusted price between March 2006 and September 2018. The return for each stock is calculated for each quarter. The current quarter's weight is compared with the previous quarter's return-adjusted weight for each stock. Institutional investor is classified as a buyer (seller) if his end of the quarter weight of the stock in the portfolio is greater (smaller) than his previous quarter's return-adjusted stock weight. Then, the number of institutional investors that increase their return-adjusted portfolio weight as a fraction of the total institutional investors that change their return-adjusted portfolio weight for the stock is calculated. This fraction is normalized for each stock and quarter. 49 cross-sectional regressions are estimated by using the lag standardized fraction of institutions that increase their return-adjusted stock weights as the independent variable and the standardized fraction of institutions that increase their return-adjusted portfolio weights in the current quarter as the dependent variable. The estimated regression coefficients are interpreted as cross-sectional correlations because of using one independent variable and normalization of the data. The time-series averages of the 49 cross-sectional regressions' coefficients are shown in the first column of the table. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. The averages of the cross-sectional correlations are decomposed into institutions following their trades and institutions following others' trades parts and reported in the second and third columns respectively. The fourth column reports the time-series average of R^2 computed from the 49 cross-sectional regressions. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$			
Average coefficient (β)	Partitioned slope coefficient		Average R ²
	Institutions following their own trades	Institutions following others' trades	
Panel A: Stocks with ≥ 1 institution			
0.3938	0.2528	0.1410	18.99%
(11.11) ^{***}	(9.19) ^{***}	(4.48) ^{***}	
Panel B: Stocks with ≥ 5 institutions			
0.1716	0.0483	0.1234	6.40%
(5.85) ^{***}	(3.46) ^{***}	(4.32) ^{***}	
Panel C: Stocks with ≥ 10 institutions			
0.2273	0.0386	0.1887	8.63%
(7.05) ^{***}	(4.20) ^{***}	(6.49) ^{***}	
Panel D: Stocks with ≥ 15 institutions			
0.2451	0.0321	0.2131	11.07%
(6.67) ^{***}	(4.67) ^{***}	(6.42) ^{***}	
Panel E: Stocks with ≥ 20 institutions			
0.2565	0.0327	0.2238	11.20%
(7.46) ^{***}	(5.13) ^{***}	(7.29) ^{***}	

Table 13: Herding tests for institutions increasing their return-adjusted weights (All)

The portfolio weights for each stock is computed by multiplying number of stocks held in the institutional investor's portfolio with the adjusted price between March 2006 and September 2018. The return for each stock is calculated for each quarter. The current quarter's weight is compared with the previous quarter's return-adjusted weight for each stock. Institutional investor is classified as a buyer (seller) if his end of the quarter weight of the stock in the portfolio is greater (smaller) than his previous quarter's return-adjusted stock weight. Then, the number of institutional investors that increase their return-adjusted portfolio weight as a fraction of the total institutional investors that change their return-adjusted portfolio weight for the stock is calculated. This fraction is normalized for each stock and quarter. 49 cross-sectional regressions are estimated by using the lag standardized fraction of institutions that increase their return-adjusted stock weights as the independent variable and the standardized fraction of institutions that increase their return-adjusted portfolio weights in the current quarter as the dependent variable. The estimated regression coefficients are interpreted as cross-sectional correlations because of using one independent variable and normalization of the data. The time-series averages of the 49 cross-sectional regressions' coefficients are shown in the first column of the table. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. The averages of the cross-sectional correlations are decomposed into institutions following their trades and institutions following others' trades parts and reported in the second and third columns respectively. The fourth column reports the time-series average of R^2 computed from the 49 cross-sectional regressions. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$			
Average coefficient (β)	Partitioned slope coefficient		Average R ²
	Institutions following their own trades	Institutions following others' trades	
Panel A: Stocks with ≥ 1 institution			
0.3577 (14.00) ^{***}	0.2092 (6.91) ^{***}	0.1485 (6.88) ^{***}	15.89%
Panel B: Stocks with ≥ 5 institutions			
0.1208 (5.66) ^{***}	0.0067 (0.54)	0.1141 (5.55) ^{***}	4.05%
Panel C: Stocks with ≥ 10 institutions			
0.1385 (4.49) ^{***}	0.0038 (0.43)	0.1347 (4.85) ^{***}	5.97%
Panel D: Stocks with ≥ 15 institutions			
0.1734 (6.80) ^{***}	0.0039 (0.48)	0.1694 (7.38) ^{***}	7.15%
Panel E: Stocks with ≥ 20 institutions			
0.1811 (6.72) ^{***}	0.0069 (0.98)	0.1743 (7.06) ^{***}	8.12%

The same analysis is repeated for stocks with minimum 5, 10, 15 and 20 institutions. Panel B, C, D and E of Table 12 shows the results of the estimation respectively. The average correlation coefficient decreases to 17.16% for stocks with at least 5 institutions but it increases gradually and it is estimated 25.65% for stocks with 20

or more institutions. The contribution to average cross-sectional correlation from institutions following themselves part gets smaller but the contribution from institutions following others part becomes larger and it is estimated as 22.38% for stocks with at least 20 institutions. The results reveal that herding behavior among foreign institutional investors is not caused by stocks with relatively few institutions. All the estimations in Table 12 are significant at 99.99% level.

Next, the foreign and domestic institutional investors data is combined to check whether herding behavior exists due to habit investing. Table 13 presents the results of this estimation for stocks with different number of institutions. All the coefficients are higher compared to the results in Table 11. This means that some selling activities of institutions are caused by investor outflows and they are actually increasing the weights of that stocks in their portfolios.

4.5 Momentum Trading

The evidence of positive cross-sectional correlation between foreign institutional current and lagged demand may arise from the momentum trading activities of these institutions. The lagged returns are added into the model as depicted in Equations (40) to (42) to control for the momentum effect.

Table 14 shows the times series averages of the coefficients estimated from 49 cross-sectional regressions with lagged stock returns as the second independent variable for foreign institutional investors in the model. The t-statistics in parentheses are computed from Newey-West standard errors with 4 lags. Panel A shows the results for stocks with at least one trader and the average coefficient of lagged stock returns is estimated as 0.2323 and it is significant at the 99% level. Thus, one standard deviation increase (decrease) in lagged stock returns lead to a 23.23% standard deviation increase

(decrease) in the current demand of the foreign institutional investor. The foreign institutional investors implement momentum trading strategies but the correlation between lagged and current foreign institutional demand is estimated 0.3403. This estimation is very close to the estimation in Panel A of Table 10 which means that including the standardized lagged return as an independent variable in the model does not affect the average coefficient of the lagged institutional demand.

Table 14: Tests of momentum trading for institutions increasing their holdings (Foreign)

Each foreign institutional investor's holdings for each stock is computed as a fraction of the stocks' total number of shares outstanding at the end of each quarter for the period of March 2006 and September 2018. A foreign institutional investor is defined as a buyer for each stock and quarter, if its stock holdings as a fraction of total number of shares outstanding increases and a seller if it decreases compared to the previous quarter. The fraction of institutions that increase their holdings to the total number of active institutions is computed for each stock in all the quarters. This fraction is normalized for each stock and quarter. The lag quarterly stock returns are calculated and standardized. Then 49 quarterly cross-sectional regressions are estimated by using lag institutional demand and lag quarterly stock returns as independent variables, and institutional demand in the current quarter as the dependent variable. The estimated regression coefficients are interpreted as cross-sectional correlations because of the normalization of the data. The time-series averages of the 49 cross-sectional regressions' coefficients are shown in the first and second columns of the table. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. The third column reports the time-series average of R^2 computed from the 49 cross-sectional regressions. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

$\Delta_{k,t} = \beta_{1,t}\Delta_{k,t-1} + \beta_{2,t}R_{k,t-1} + \varepsilon_{k,t}$		
Average coefficient associated with lag institutional demand (β_1)	Average coefficient associated with lag return (β_2)	Average R^2
Panel A: Stocks with ≥ 1 institution		
0.3403 (13.60)***	0.2323 (2.73)**	14.42%
Panel B: Stocks with ≥ 5 institutions		
0.2185 (12.81)***	0.4617 (5.60)***	8.84%
Panel C: Stocks with ≥ 10 institutions		
0.2269 (8.87)***	0.5572 (4.83)***	10.90%
Panel D: Stocks with ≥ 15 institutions		
0.2379 (6.79)***	0.6373 (3.87)***	13.58%
Panel E: Stocks with ≥ 20 institutions		
0.2589 (8.99)***	0.4054 (2.65)**	12.87%

The same analysis is repeated for stocks with minimum 5, 10, 15 and 20 institutions for controlling the effect of stocks with few institutions. Panel B, C, D and E of Table 14 show the results of these estimations. The times-series average of the lagged return coefficient of 49 cross-sectional regressions increase to 0.4617 for stocks with at least 5 institutions. The effect of lagged returns gets stronger as the number of institutions is increased but the coefficient of lagged institutional demand remains close to the estimation in Table 10. The times-series average of the lagged return coefficient of 49 cross-sectional regressions is estimated 0.5572 for stocks with at least 10 institutions and 0.6373 for stocks with at least 15 institutions. The average correlation decreases to 0.4054 for stocks with at least 20 institutions. The average correlation between current and lagged foreign institutional demand is estimated at 0.2185, 0.2269, 0.2379 and 0.2589 for stocks with at least 5, 10, 15 and 20 institutions. All these estimations are significant at 99.99%. Thus, the foreign institutions are implementing aggressive momentum trading strategies, but these strategies do not cause a herding behavior.

Table 15 reports the results of the same analysis for both local and foreign institutions. The results also reveal that the institutional investors' demand in the current quarter has positive relation with the stock returns and institutional demand of the previous quarter. However, the stock returns of the previous quarter do not cause the institutional herding. The analysis is repeated for the standardized fraction of institutions that increase their return-adjusted portfolio weights and the results do not change. Table 16 shows the results of the estimations for foreign institutions only. There is a positive correlation between lagged returns and the current period's standardized fraction of institutions that increase their return-adjusted portfolio weights. The foreign institutions implement momentum trading strategies but these strategies are not the primary reason of institutional herding. The results of the same analysis for both local and foreign

institutions are shown in Table 17. The results support the evidence that the institutional demand in BIST is strongly related to lagged stock returns. But, the effect of the previous quarter's lagged institutional demand remains stable after taking into account the momentum trading strategies.

Table 15: Tests of momentum trading for institutions increasing their holdings
(All)

Each institutional investor's holdings for each stock is computed as a fraction of the stocks' total number of shares outstanding at the end of each quarter for the period of March 2006 and September 2018. An institutional investor is defined as a buyer for each stock and quarter, if its stock holdings as a fraction of total number of shares outstanding increases and a seller if it decreases compared to the previous quarter. The fraction of institutions that increase their holdings to the total number of active institutions is computed for each stock in all the quarters. This fraction is normalized for each stock and quarter. The lag quarterly stock returns are calculated and standardized. Then 49 quarterly cross-sectional regressions are estimated by using lag institutional demand and lag quarterly stock returns as independent variables, and institutional demand in the current quarter as the dependent variable. The estimated regression coefficients are interpreted as cross-sectional correlations because of the normalization of the data. The time-series averages of the 49 cross-sectional regressions' coefficients are shown in the first and second columns of the table. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. The third column reports the time-series average of R^2 computed from the 49 cross-sectional regressions. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

$\Delta_{k,t} = \beta_{1,t}\Delta_{k,t-1} + \beta_{2,t}R_{k,t-1} + \varepsilon_{k,t}$		
Average coefficient associated with lag institutional demand (β_1)	Average coefficient associated with lag return (β_2)	Average R^2
Panel A: Stocks with ≥ 1 institution		
0.2870 (12.04)***	0.3941 (6.30)***	10.78%
Panel B: Stocks with ≥ 5 institutions		
0.1050 (5.64)***	0.5043 (5.33)***	4.46%
Panel C: Stocks with ≥ 10 institutions		
0.1414 (6.98)***	0.4850 (4.23)***	6.34%
Panel D: Stocks with ≥ 15 institutions		
0.1735 (10.29)***	0.5696 (4.11)***	8.08%
Panel E: Stocks with ≥ 20 institutions		
0.1819 (8.81)***	0.5625 (4.27)***	8.43%

Table 16: Tests of momentum trading for institutions their return-adjusted weights (Foreign)

The portfolio weights for each stock is computed by multiplying number of stocks held in the institutional investor's portfolio with the adjusted price between March 2006 and September 2018. The return for each stock is calculated for each quarter. The current quarter's weight is compared with the previous quarter's return-adjusted weight for each stock. Institutional investor is classified as a buyer (seller) if his end of the quarter weight of the stock in the portfolio is greater (smaller) than his previous quarter's return-adjusted stock weight. Then, the number of institutional investors that increase their return-adjusted portfolio weight as a fraction of the total institutional investors that change their return-adjusted portfolio weight for the stock is calculated. This fraction is normalized for each stock and quarter. The lag quarterly stock returns are calculated and standardized. 49 cross-sectional regressions are estimated by using the lag standardized fraction of institutions that increase their return-adjusted stock weights and lag quarterly stock returns as the independent variables and the standardized fraction of institutions that increase their return-adjusted portfolio weights in the current quarter as the dependent variable. The estimated regression coefficients are interpreted as cross-sectional correlations because of the normalization of the data. The time-series averages of the 49 cross-sectional regressions' coefficients are shown in the first and second columns of the table. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. The third column reports the time-series average of R^2 computed from the 49 cross-sectional regressions. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

$\Delta_{k,t} = \beta_{1,t}\Delta_{k,t-1} + \beta_{2,t}R_{k,t-1} + \varepsilon_{k,t}$		
Average coefficient associated with lag institutional demand (β_1)	Average coefficient associated with lag return (β_2)	Average R^2
Panel A: Stocks with ≥ 1 institution		
0.3901 (10.87)***	0.2260 (3.72)***	19.86%
Panel B: Stocks with ≥ 5 institutions		
0.1658 (5.71)***	0.3903 (6.17)***	7.78%
Panel C: Stocks with ≥ 10 institutions		
0.2188 (6.94)***	0.4061 (4.58)***	10.31%
Panel D: Stocks with ≥ 15 institutions		
0.2362 (6.35)***	0.4982 (4.52)***	13.23%
Panel E: Stocks with ≥ 20 institutions		
0.2489 (6.68)***	0.5316 (3.91)***	13.64%

Table 17: Tests of momentum trading for institutions their return-adjusted weights (All)

The portfolio weights for each stock is computed by multiplying number of stocks held in the institutional investor's portfolio with the adjusted price between March 2006 and September 2018. The return for each stock is calculated for each quarter. The current quarter's weight is compared with the previous quarter's return-adjusted weight for each stock. Institutional investor is classified as a buyer (seller) if his end of the quarter weight of the stock in the portfolio is greater (smaller) than his previous quarter's return-adjusted stock weight. Then, the number of institutional investors that increase their return-adjusted portfolio weight as a fraction of the total institutional investors that change their return-adjusted portfolio weight for the stock is calculated. This fraction is normalized for each stock and quarter. The lag quarterly stock returns are calculated and standardized. 49 cross-sectional regressions are estimated by using the lag standardized fraction of institutions that increase their return-adjusted stock weights and lag quarterly stock returns as the independent variables and the standardized fraction of institutions that increase their return-adjusted portfolio weights in the current quarter as the dependent variable. The estimated regression coefficients are interpreted as cross-sectional correlations because of the normalization of the data. The time-series averages of the 49 cross-sectional regressions' coefficients are shown in the first and second columns of the table. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. The third column reports the time-series average of R^2 computed from the 49 cross-sectional regressions. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

$\Delta_{k,t} = \beta_{1,t}\Delta_{k,t-1} + \beta_{2,t}R_{k,t-1} + \varepsilon_{k,t}$		
Average coefficient associated with lag institutional demand (β_1)	Average coefficient associated with lag return (β_2)	Average R^2
Panel A: Stocks with ≥ 1 institution		
0.3572 (13.89)***	0.3368 (7.21)***	16.87%
Panel B: Stocks with ≥ 5 institutions		
0.1217 (5.74)***	0.4648 (5.81)***	5.83%
Panel C: Stocks with ≥ 10 institutions		
0.1355 (4.40)***	0.5010 (5.40)***	7.93%
Panel D: Stocks with ≥ 15 institutions		
0.1695 (6.72)***	0.4999 (4.71)***	9.41%
Panel E: Stocks with ≥ 20 institutions		
0.1793 (6.74)***	0.4825 (4.30)***	9.86%

4.6 Institutional Demand & Subsequent Stock Returns

The correlations between raw fraction of institutional buyers in the current quarter (Equation (32)) and stock returns computed for the previous quarter, the current quarter, the following quarter, the following six months and the following twelve months are analyzed to evaluate whether the herding behavior is driven by non-informational motives or informational motives. If the herding behavior is driven by non-informational motives like fads, reputational concerns or characteristics herding, then there should be a negative relation between current institutional demand and future returns. The evidence of return reversal in the future periods is considered as a herding behavior driven by non-informational motivations. If the herding behavior is driven by informational motivations, then there should be a weak positive relation between current institutional demand and the future returns.

Table 18 shows the results of correlations between current foreign institutional demand and stock returns for various periods. There is a positive correlation between the fraction of foreign institutional buyers in the current quarter and the previous quarter returns for stocks with different number of institutions. The correlation is 10.29% for stocks with at least one trader, and it increases to 13.84% for stocks with at least 5 institutions, 13.14% for stocks with at least 10 institutions, 13.54% for stocks with at least 15 institutions, and 13.24% for stocks with at least 20 institutions. The correlation between foreign institutional demand in the current period and stock returns in the same period is also positive. The correlation is estimated as 6.96% for stocks with at least one trader. This correlation increases monotonically as we increase the number of institutions and it reaches to 18.65% for stocks with at least 20 institutions. These correlations are in line with the evidence of momentum trading in the previous section. The correlations

between foreign institutional demand in the current period and future period stock returns are all positive but all the correlation estimations are insignificant. There is no evidence of return reversal in the future periods for the sample period. The lack of return reversal eliminates the case for herding driven by non-informational motivations for the foreign institutional investors.

Table 18: Correlations between institutional demand & stock returns (Foreign)

Each foreign institutional investor's holdings for each stock is computed as a fraction of the stocks' total number of shares outstanding at the end of each quarter for the period of March 2006 and September 2018. A foreign institutional investor is defined as a buyer for each stock and quarter, if its stock holdings as a fraction of total number of shares outstanding increases and a seller if it decreases compared to the previous quarter. The fraction of institutions that increase their holdings to the total number of active institutions is computed for each stock in all the quarters. The cross-sectional correlations between the fraction of institutions buying in the current quarter and stock returns of the previous quarter, the current quarter, the following quarter, the following six months and the following twelve months are computed. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

Sample	Previous quarter return	Same quarter return	Following quarter return	Following 6-month return	Following 12-month return
≥ 1 institution	0.1029 (5.27)***	0.0696 (4.27)**	0.0071 (0.43)	0.0087 (0.53)	0.0195 (0.98)
≥ 5 institutions	0.1383 (7.09)***	0.1302 (5.59)***	0.0182 (0.83)	0.0021 (0.07)	0.0083 (0.25)
≥ 10 institutions	0.1314 (6.83)***	0.1464 (5.78)***	0.0261 (0.99)	0.0169 (0.54)	0.0260 (0.75)
≥ 15 institutions	0.1354 (6.46)***	0.1750 (7.92)***	0.0436 (1.47)	0.0474 (1.37)	0.0221 (0.61)
≥ 20 institutions	0.1324 (4.73)***	0.1865 (8.86)***	0.0311 (1.23)	0.0297 (0.85)	0.0286 (0.73)

The same analysis is repeated for both domestic and foreign institutional investors and the results are presented in Table 19. The positive correlation between the fraction of all institutional buyers in the current quarter and the previous quarter returns for stocks with different number of institutions still exists. The correlation is 7.59% for stocks with at least one trader and it is significant at the 99.99%. The correlation increases to 13.10% for stocks with at least 20 institutions. The correlation between the fraction of institutional

buyers in the current quarter and current quarter stock returns becomes insignificant except for stocks with at least 20 institutions. The correlation is 3.45% and it is significant at the 95% level. The correlation is positive for future period returns but they are not significant. There is no evidence of the return reversal in the future returns for all institutions combined.

Table 19: Correlations between institutional demand & stock returns (All)

Each institutional investor's holdings for each stock is computed as a fraction of the stocks' total number of shares outstanding at the end of each quarter for the period of March 2006 and September 2018. An institutional investor is defined as a buyer for each stock and quarter, if its stock holdings as a fraction of total number of shares outstanding increases and a seller if it decreases compared to the previous quarter. The fraction of institutions that increase their holdings to the total number of active institutions is computed for each stock in all the quarters. The cross-sectional correlations between the fraction of institutions buying in the current quarter and stock returns of the previous quarter, the current quarter, the following quarter, the following six months and the following twelve months are computed. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

Sample	Previous quarter return	Same quarter return	Following quarter return	Following 6-month return	Following 12-month return
≥ 1 institution	0.0759 (4.71)***	-0.0071 (-0.33)	0.0071 (0.43)	0.0065 (0.42)	0.0084 (0.39)
≥ 5 institutions	0.1309 (7.39)***	-0.0394 (-0.19)	0.0184 (0.99)	0.0051 (0.23)	0.0050 (0.21)
≥ 10 institutions	0.1168 (5.20)***	0.0226 (1.13)	0.0190 (0.90)	0.0086 (0.34)	0.0259 (0.90)
≥ 15 institutions	0.1226 (5.47)***	0.0335 (1.72)	0.0301 (1.27)	0.0258 (1.07)	0.0372 (1.43)
≥ 20 institutions	0.1310 (5.55)***	0.0345 (2.30)*	0.0306 (1.14)	0.0126 (0.49)	0.0272 (1.09)

4.7 Herding by Firm Size

The results in the previous section reveal that herding behavior of foreign institutional investors is driven by information. To decide whether information cascades or investigative herding is the main reason of this herding behavior driven by information, the data is divided into size quintiles. In each quarter the stocks are sorted by their market capitalizations and divided into five quintiles. For each quarter and size quantile, the raw fraction of buyers for each stock is calculated as in Equation (32) and then normalized as in Equation (33). Total of 49 cross-sectional regressions are estimated within each capitalization quintile as shown in Equation (34). The independent variable of the cross-sectional regressions is the lagged domestic institutional demand and the dependent variable is the current quarter's domestic institutional demand. The averages of the cross-sectional correlations are partitioned into institutions following their own trades and institutions following others' trades parts, as shown in Equation (35).

Table 20 reports the time-series averages of the 49 cross-sectional regressions for each size quintile. The first column of the table shows the average coefficient for small size stocks and it is estimated 0.3154. The second and third columns give the average coefficients from the decomposition of the average into the foreign institutions following themselves and others parts. The average coefficient of foreign institutions following themselves is estimated 0.1739. The high coefficient means that the foreign institutions distribute their trading activity throughout time as the liquidity in the small size stocks is low compared to the portfolio sizes of the foreign institutions. The average coefficient for foreign institutions following others is estimated 0.1415 and it is significant at the 99.99% level. The average coefficient for the second quintile decreases to 0.2331 but the average coefficient of foreign institutions following others is estimated 0.1271. The average

coefficient for the third size quintile is estimated 0.2343 but share of foreign institutions following themselves decrease to 0.0321. The foreign institutions following others coefficient increases to 0.2022. The herding behavior exists for the third quintile among foreign institutions and it is stronger compared to the relatively smaller stocks. For the fourth quintile, the average coefficient decreases to 0.1326 and the coefficient of institutions following others decrease to 0.1159 and becomes insignificant. The lowest level of significance is taken at the 95% level in the analysis, but the estimation becomes significant at the 90% confidence level. For the last quintile of the stocks with largest market capitalization, the average coefficient is estimated 0.2019 and the decomposition shows that 0.0219 of the correlation emerges from institutions following themselves, while 0.1801 of the correlation emerges from institutions following others. There is a herding behavior among the local institutional investors in small size stocks and it is interpreted as herding driven by informational cascades in Chapter III. There is also a contrarian investment behavior for large capitalization stocks among local institutional investors. The results for foreign investors show that herding behavior exists for small size stocks and it is stronger compared to domestic institutional investors. The herding behavior in small size stocks is arising from informational cascades which means that inferring from the trading decisions of other institutions. As the market capitalization of stocks increase, the herding behavior continues and this herding behavior results from investigative herding. The foreign institutional investors rely more on financial and economic indicators compared to domestic institutions as they follow the domestic market from abroad. There is more information produced for large stocks as more analysts and market commentators are watching these stocks and the foreign institutional investors react to new signals together and this creates an investigative herding in large stocks. On the other hand, the domestic institutional investors have more chance to obtain private

information due to the proximity to the market and the firms, and they form their own private information to use in implementing contrarian trading strategies.

Table 20: Herding and following their own trades by capitalization quantile (Foreign)

Each foreign institutional investor's holdings for each stock is computed as a fraction of the stocks' total number of shares outstanding at the end of each quarter for the period of March 2006 and September 2018. A foreign institutional investor is defined as a buyer for each stock and quarter, if its stock holdings as a fraction of total number of shares outstanding increases and a seller if it decreases compared to the previous quarter. The fraction of institutions that increase their holdings to the total number of active institutions is computed for each stock in all the quarters. This fraction is normalized for each stock and quarter. Stocks that have at least one active trader are sorted and divided into five size quintiles for each quarter. Then, total of 49 cross-sectional regressions are estimated within each capitalization quintile. The independent variable of the cross-sectional regressions is the lagged foreign institutional demand and the dependent variable is the current quarter's foreign institutional demand. The estimated regression coefficients are interpreted as cross-sectional correlations because of using one independent variable and normalization of the data. The time-series averages of the 49 cross-sectional regressions' coefficients are shown in the first column of the table. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. The averages of the cross-sectional correlations are decomposed into institutions following their trades and institutions following others' trades parts and reported in the second and third columns respectively. The fourth column reports the time-series average of R^2 computed from the 49 cross-sectional regressions. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

Capitalization quintile	Average coefficient (β)	Partitioned slope coefficient		Average R^2
		Institutions following their own trades	Institutions following others' trades	
Small firms	0.3154 (14.12)***	0.1739 (10.45)***	0.1415 (7.26)***	12.34%
Quintile 2	0.2331 (6.25)***	0.1059 (5.04)***	0.1271 (3.88)***	12.12%
Quintile 3	0.2343 (4.98)***	0.0321 (2.21)*	0.2022 (4.30)***	16.11%
Quintile 4	0.1326 (2.19)*	0.0167 (1.57)	0.1159 (1.90)	19.31%
Large firms	0.2019 (2.71)**	0.0219 (4.31)***	0.1801 (2.43)*	30.81%

Table 21 shows the results of the same analysis for both local and foreign institutional investors. The time-series average for the coefficient of investors following each other in smaller market capitalization quintiles are 0.1388 and 0.1516. The herding behavior due to information cascades still exists for domestic and foreign institutional investors combined. The herding behavior disappears as the market capitalization of

stocks increases except for the fourth quintile. The time-series average of the correlation between institutional demand in the current and the previous quarter is estimated 0.1742. 2.64% of this correlation comes from institutions following themselves and 14.79% of the correlation results from institutions following others. The results of the stand-alone analysis for domestic and foreign institutions do not indicate a herding behavior for this quintile. The evidence of herding in this quintile demonstrates that domestic and foreign institutions follow the same signals coming from stocks in this quintile.

Table 21: Herding and following their own trades by capitalization quintile (All)

Each institutional investor's holdings for each stock is computed as a fraction of the stocks' total number of shares outstanding at the end of each quarter for the period of March 2006 and September 2018. An institutional investor is defined as a buyer for each stock and quarter, if its stock holdings as a fraction of total number of shares outstanding increases and a seller if it decreases compared to the previous quarter. The fraction of institutions that increase their holdings to the total number of active institutions is computed for each stock in all the quarters. This fraction is normalized for each stock and quarter. Stocks that have at least one active trader are sorted and divided into five size quintiles for each quarter. Then, total of 49 cross-sectional regressions are estimated within each capitalization quintile. The independent variable of the cross-sectional regressions is the lagged institutional demand and the dependent variable is the current quarter's institutional demand. The estimated regression coefficients are interpreted as cross-sectional correlations because of using one independent variable and normalization of the data. The time-series averages of the 49 cross-sectional regressions' coefficients are shown in the first column of the table. The t-statistics that are computed by using Newey-West standard errors with 4 lags and they are presented in parentheses. The averages of the cross-sectional correlations are decomposed into institutions following their trades and institutions following others' trades parts and reported in the second and third columns respectively. The fourth column reports the time-series average of R^2 computed from the 49 cross-sectional regressions. ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% level respectively.

Capitalization quintile	Average coefficient (β)	Partitioned slope coefficient		Average R^2
		Institutions following their own trades	Institutions following others' trades	
Small firms	0.2669 (9.79)***	0.1281 (5.03)***	0.1388 (9.28)***	8.64%
Quintile 2	0.2064 (4.21)***	0.0547 (1.92)	0.1516 (3.69)***	9.03%
Quintile 3	0.1129 (2.25)*	0.0245 (0.82)	0.0884 (1.42)	13.41%
Quintile 4	0.1742 (3.15)**	0.0264 (1.30)	0.1479 (2.45)*	18.71%
Large firms	0.1206 (1.67)	0.0075 (0.98)	0.1130 (1.68)	31.28%

4.8 Returns Comparison

The analysis of herding behavior reveals that domestic and foreign institutions tend to herd in relatively small stocks. There is a differentiation of behavior in large capitalization stocks. The domestic institutional investors implement contrarian investment strategy and the foreign institutional investors herd due to following the same signals. In this section, the effect of this difference in behavior on the stock returns will be analyzed. For each quarter, the raw fraction of institutions that are buyers are calculated as in Equation (32) and then standardized as in Equation (33). Then the stocks are sorted according to the standardized raw fraction of buyers and are divided into five quintiles in each quarter. The stocks in the first quintile are the stocks that have the lowest level of the standardized raw fraction of buyers. Since one minus the standardized raw fraction of buyers also means the standardized raw fraction of sellers, the stocks in the first quintile are the ones that are heavily sold by institutional investors. The stocks in the fifth quintile are the stocks that are heavily bought by institutional investors. Then, quarterly holding period returns are calculated from the adjusted prices of each stock, and the equal-weighted averages of the stock returns are computed for each quarter.

Table 22 reports the results of the return analysis for stocks with at least 1,5,10,15 and 20 institutions. The first column shows the standardized raw fraction of buyers' quintiles. The second and the third columns are the average quarterly returns of stocks traded by local and foreign institutional investors respectively. The last column gives the differences of returns for these investors. Panel A of the table shows the results for stocks with at least 1 trader. The average return of heavily sold stocks for domestic institutional investors is 6.70%, and 1.10% for foreign institutional investors. The average return difference is 5.10% but it is not significant. As the standardized raw fraction of buyers

increases, the average return of stocks traded by domestic institutional investors decreases and the average return of stocks traded by foreign institutional investors increases. The average returns of heavily bought stocks are 2.77% for domestic investors, and 5.10% for foreign investors. The return difference is -2.33%, but it is not significant. In Panel B, the average return of stocks for local institutions is 7.59% for heavily sold stocks. The average return for foreign institutions is 1.28% and the return difference is 6.31% and significant at the 95% level. The average returns for heavily bought stocks are 1.22% for locals and 6.69% for foreign institutions. The average return difference is -5.47% but it is insignificant. The results in Panel C show that the average return of heavily sold stocks for domestic institutions rises to 8.12%. The average return for foreign institutions is 1.10%. The average return of heavily bought stocks is -0.24% and 7.11% for domestic and foreign institutions respectively. The average return difference is 7.02% for the heavily sold stocks and -7.34% for the heavily bought stocks and they are all significant at the 95% level. In Panel D of the table, the average returns of the heavily sold stocks are 8.09% for locals and 0.65% for foreign investors. The return difference is 7.43% and it is significant at the 95% level. The average return of heavily bought stocks decreases to -1.05% for domestic institutions and increases to 7.07% for foreign institutions. The difference of returns is -8.12% and it is significant at the 99% level. Lastly, Panel D of the table shows the results for stocks with at least 20 institutions. The average return of the heavily sold stocks is 9.68% for domestic institutions, while it is 0.65% for foreign institutions. The return difference is 8.77% and it is significant at the 99% level. On the other hand, the return of the stocks that are bought heavily by the local institutions is -0.70%. The return of the stocks that are bought heavily by the foreign institutions is 7.17%. The return difference is -7.88% and it is also significant at the 99% level.

Table 22: Comparison of returns for domestic and foreign institutions

For each security and quarter between March 2006 and September 2018, the fraction of institutional institutions that increase their position in the security is calculated. An investor is defined as increasing his position if that investor holds a greater fraction of the firm's outstanding shares at the end of the quarter than it was held at the end of the previous quarter. All data are standardized (i.e., rescaled to zero mean, unit variance) each quarter. Then, the stocks are sorted according to the standardized raw fraction of buyers and are divided into five quintiles in each quarter. The first quintile shows the stocks that are heavily sold, and the last quintile that are heavily bought. The quarterly holding period returns are calculated for both domestic and foreign institutions from the adjusted prices of each stock, and the equally-weighted averages of returns are computed for each quarter. Lastly, the difference of average returns for domestic and foreign institutions are computed. The associated t-statistics are presented in parentheses. *** Indicates statistical significance at the 0.1% level; ** indicates statistical significance at the 1% level; * indicates statistical significance at the 5% level.

Standardized Raw Fraction of Buyers Quintiles	Local Returns	Foreign Returns	Difference
Panel A: Stocks with ≥ 1 institution			
Heavily Sold	0.0670 (3.39)***	0.0110 (0.53)	0.0560 (1.96)
Quintile 2	0.0385 (2.01)	0.0252 (1.20)	0.0133 (0.47)
Quintile 3	0.0298 (1.46)	0.0466 (2.41)*	-0.0169 (-0.60)
Quintile 4	0.0178 (0.89)	0.0582 (2.98)**	-0.0403 (-1.45)
Heavily Bought	0.0277 (1.56)	0.0510 (2.52)*	-0.0233 (-0.86)
Panel B: Stocks with ≥ 5 institutions			
Heavily Sold	0.0759 (3.50)***	0.0128 (0.59)	0.0631 (2.02)*
Quintile 2	0.0440 (2.10)*	0.0202 (0.96)	0.0238 (0.80)
Quintile 3	0.0372 (1.98)	0.0367 (1.73)	0.0004 (0.02)
Quintile 4	0.0132 (0.62)	0.0544 (2.73)**	-0.0411 (-1.42)
Buyers	0.0122 (0.60)	0.0669 (3.09)**	-0.0547 (-1.84)

Table 22 (continued).

Standardized Raw Fraction of Buyers Quintiles	Local Returns	Foreign Returns	Difference
Panel C: Stocks with ≥ 10 institutions			
Heavily Sold	0.0812 (3.67) ^{***}	0.0110 (0.50)	0.0702 (2.25) [*]
Quintile 2	0.0432 (1.97)	0.0222 (1.06)	0.0210 (0.69)
Quintile 3	0.0353 (1.72)	0.0323 (1.57)	0.0032 (0.11)
Quintile 4	0.0210 (1.04)	0.0530 (2.57) [*]	-0.0320 (-1.11)
Heavily Bought	-0.0024 (-0.12)	0.0711 (3.36) ^{**}	-0.0734 (-2.51) [*]
Panel D: Stocks with ≥ 15 institutions			
Heavily Sold	0.0809 (3.39) ^{**}	0.0065 (0.31)	0.0743 (2.35) [*]
Quintile 2	0.0520 (2.55) [*]	0.0187 (0.85)	0.0333 (1.11)
Quintile 3	0.0215 (1.03)	0.0362 (1.70)	-0.0147 (-0.49)
Quintile 4	0.0243 (1.12)	0.0437 (2.14) [*]	-0.0195 (-0.65)
Heavily Bought	-0.0105 (-0.58)	0.0707 (3.11) ^{**}	-0.0812 (-2.79) ^{**}
Panel E: Stocks with ≥ 20 institutions			
Heavily Sold	0.0968 (4.46) ^{***}	0.0091 (0.40)	0.0877 (2.78) ^{**}
Quintile 2	0.0367 (1.65)	0.0204 (0.98)	0.0163 (0.54)
Quintile 3	0.0340 (1.50)	0.0365 (1.73)	-0.0026 (-0.59)
Quintile 4	0.0210 (0.96)	0.0430 (2.05) [*]	-0.0220 (-0.72)
Heavily Bought	-0.0070 (-0.38)	0.0717 (3.28) ^{**}	-0.0788 (-2.76) ^{**}

The analysis above confirms the differences of behavior between domestic and foreign institutions in terms of returns. The domestic investors implement negative feedback trading strategies and sell the stocks that are overperforming and buy the stocks that are underperforming. The foreign institutions implement positive feedback trading strategies and buy the stocks that are overperforming and sell the stocks that are underperforming. The return differences get stronger for stocks with more institutions. This difference in behavior is a main contribution to the literature. There are various studies that confirm foreign investors implement positive feedback trading strategies in emerging markets. Borensztein & Gelos [153] find evidence of positive feedback trading for emerging market equity mutual funds. The positive feedback trading strategies of foreign funds are identified for South Korea ([99]), Brazil ([154]), India ([155]), Taiwan (Hsieh [156]), Thailand ([157]), and Vietnam ([158]). However, Ülkü [159] shows that foreign investors exhibit negative feedback trading strategies in European emerging stocks. The previous studies on Turkey identify negative feedback trading strategies implemented by foreign investors. Adabağ & Ornelas ([160]) find evidence of foreign investors' negative feedback trading for the period of 1997-2004, Akar [161] for the period of 1997-2007, Ülkü & İkizerli ([162]) for the period of 1997-2011, and Adaoğlu & Katırcıoğlu [163] for the period of 1997-2010. Somuncu & Karan [138] provide evidence that local investors engaged in positive feedback trading for the period of 2001-2004, whereas foreign investors engaged in negative feedback trading for the same period. The difference between this study and previous studies may result from the informational asymmetries between domestic institutions and foreign institutions. The domestic institutions may have an advantage in gathering information compared to foreign institutions. This difference in the behaviors of domestic and foreign institutions may result from the information asymmetries that they are facing.

4.9 Conclusion

The institutional investors may engage in a herding behavior due to reputational concerns, investing in stocks with the same characteristics, implementing positive feedback trading strategies, following the same signals in the market, and fads. This study investigates the herding behavior of domestic and foreign institutional investors for the period of March 2006-September 2018 by using the measure developed by Sias [1]. The results show that domestic institutions herd in stocks that have few institutions and small in capitalization. On the other hand, the herding measure is estimated higher for the foreign investors and it exists for stocks with different number of institutions and for both small and large-capitalization stocks. The herding behavior of both institutions is not driven by characteristics herding. The foreign institutions use momentum trading strategies aggressively compared to domestic institutions, but the herding behavior is not caused by these strategies. The analysis of current institutional demand and future stock returns provides evidence in favor of herding driven by informational motivations. The lack of any destabilizing effect of the current institutional demand on future stock returns and the absence of return reversals supports the hypothesis of herding driven by informational cascades and investigative herding. The evidence of positive feedback trading strategies of foreign institutions and negative feedback trading strategies of domestic institutions are analyzed in detail in terms of returns. This return analysis may help finance professionals in designing trading strategies.

CHAPTER V

CONCLUSION

This chapter will conclude the study by summarizing the key findings in relation to the herding behavior of both domestic and foreign institutional investors in Borsa İstanbul (BİST). This thesis is the first study in the literature that explains the herding behavior among domestic and foreign institutions in Turkish stock market by using the methodology proposed by Sias [1]. It will also review the limitations of the study and propose opportunities for future research.

Several theories have been proposed in the literature to explain institutional herding behavior, namely investigative herding, informational cascades, characteristic herding, reputational herding and fads. The first two theories are based on information and the last three of them are non-informational. Investigative herding emerges when institutional investors receive correlated signals and trade on these signals. Informational cascades occur when the institutional investors infer information from the prior trades of other institutional investors and follow their trades. Reputational herding arises if institutional investors follow each other due to reputational concerns. If institutional investors are attracted to securities with certain characteristics, this may result in characteristics herding. Fads and hype among institutional investors are other sources of herding behavior. This study is aimed to search for evidence of herding behavior and explain the motivation behind it by using the theories stated above.

I start the analysis with the estimation of cross-sectional correlations between institutional demand in current quarter and the lagged institutional demand for stocks with different number of actively trading institutions. These estimated cross-sectional correlations are further decomposed into institutions following their own trades and institutions following others' trades parts. Institutions following others' part is the herding measure of the Sias [1] in the analysis. I find a positive cross-sectional correlation between the current and the lagged domestic institutional demand for stocks with at least one active institution. The results of the decomposition are positive and significant, which is interpreted as evidence of herding is found among domestic institutions. The average cross-sectional correlations are found to be negative for stocks with higher number of actively trading institutions. This negativity arises from institutions following their own trades term. The evidence of herding disappears for stocks with higher number of actively trading institutions. Thus, herding behavior among domestic institutions are driven by stocks traded by relatively few institutions. The estimation results for foreign institutions are positive and larger in magnitude compared to domestic institutions in every category. There is a stronger evidence of herding among foreign institutional investors and it increases monotonically as the number of actively trading institutions increases. The foreign institutions may have a higher tendency to herd compared to domestic institutions. They may face higher reputational costs due to intense competition and less job security. They may not trust their own private information due to high informational asymmetries and follow the prior trades of the others. They may follow the same signals and have a higher tendency to enter into correlated trades with the others. They may also be attracted to stocks with certain characteristics. The results for foreign institutions have stronger economic significance compared to the study of Sias [1]. The information in emerging markets are more asymmetric than the developed markets. This informational asymmetry

may cause the institutions to herd by following the trades of others. The liquidity is also lower in emerging markets than developed markets. The foreign institutions that have large portfolio sizes may distribute their trades over time to reduce the effect of their trading on the market price. Following their own trades and following others' trades coefficients of foreign institutions may be higher due to low liquidity in the market.

Characteristic herding results in institutional investors holding similar portfolios. Sias [1] defines "habit investing" as a special case of characteristic herding arising from the positive cross-sectional and time-series correlations of net flows to the institutions. I examine the changes in stock allocations to determine whether herding behavior is driven by the institutions' net flows. The positive and significant cross-sectional correlations between the standardized fraction of institutional investors increasing their return-adjusted portfolio weights in the current quarter and the standardized fraction of institutional investors increasing their return-adjusted portfolio weights in the previous quarter indicate that habit investing is not the source of herding behavior for domestic and foreign institutional investors.

Momentum is a stock characteristic that institutional investors may prefer to have in their portfolios. The evidence of herding behavior may arise from momentum trading strategies of institutional investors. The lagged stock returns are added into the analysis for controlling momentum effect. The results reveal that foreign institutions engage in momentum trading strategies more aggressively than the domestic institutions. However, economically and statistically significant cross-sectional correlations between current and lagged institutional demand reveal that the herding behavior is not affected from the momentum trading strategies of institutions.

The cross-sectional correlations between current institutional demand and future periods' stock returns are investigated to differentiate between non-informational and informational herding theories. If the herding behavior is caused by non-informational motivations, then there should be a return reversal in the future periods. However, I do not find any significant correlations between current institutional demand and future stock returns for domestic and foreign institutions. The lack of return reversal evidence eliminates the theories of herding based on non-informational motivations. The cross-sectional correlations between institutional demand and the stock returns of the previous and current quarters are positive for foreign institutions. This finding is expected as these investors implement momentum trading strategies aggressively. However, there is a weak positive relation between current institutional demand and previous quarters' stock returns for domestic institutions. The cross-sectional correlations between current institutional demand and stock returns turn to negative for domestic institutions. This negative finding increases monotonically for stocks with higher number of actively trading domestic institutions. However, Sias [1] found a positive relation between current institutional demand and stock returns. This finding means that domestic institutions are buying the stocks that are underperforming and selling the stocks that are overperforming, indicating a contrarian investment strategy.

To decide whether information cascades or investigative herding is the main motivation of herding behavior, the stocks in each quarter are sorted and divided into size quintiles. If herding arises from inferring information from the prior trades of others (informational cascades), then herding should be higher in small-capitalization stocks. The information in small stocks is limited because of low analyst interest and less media coverage. The private information is noisier in these stocks and can be ignored by following the trades of the others. If herding arises from following the same signals and

entering into correlated trades, then herding should be higher in large-capitalization stocks. There are multiple analysts that cover the large stocks and their media coverage is higher compared to small stocks. The changes in information are followed by many institutions and the institutions may react to new information by trading in the same way. The analysis by stock size for domestic investors shows that institutional herding exists only in small stocks and disappears as stock size increases. Furthermore, the evidence of negative coefficient is found for following their own trades and following others' trades in the highest market-capitalization quintile. Thus, domestic institutions tend to sell (buy) the stocks that they bought (sold) in the previous quarter. This is the main finding of this study that is different than Sias [1]'s findings. The same analysis for foreign institutions indicates that herding behavior exists in both small and large stocks. The coefficient of institutions following their own trades is highest in small-capitalization stocks. This finding is consistent with the hypothesis of low liquidity concerns of foreign institutions.

The differences of trading behavior in large-capitalization quintile is further analyzed by comparing the returns. The return comparison shows that domestic institutions sell (buy) the stocks that are over-performing (under-performing). On the contrary, the foreign institutions buy (sell) the stocks that are over-performing (underperforming). Thus, domestic institutions are implementing negative feedback trading strategies. However, the foreign institutions implement positive feedback trading strategies. This difference in behavior may result from the informational asymmetries between domestic institutions and foreign institutions. Furthermore, it may be the main factor in balancing the impact of foreign institutional demand on the future stock returns.

This study has potential limitations. The herding measure of Sias [1] assumes that there are no short-selling restrictions in the market. However, short-selling can be costlier in emerging markets and institution may refrain from using. Furthermore, Sias [1]'s

measure uses number of buyers and sellers without considering the trading volume. The hypothesis of herding behavior driven by reputational concerns is rejected due to lack of return reversal in stocks' future returns. The assumption of inverse relation between institutional demand and future stock returns in reputational herding case is very strong. The reputational herding may not create a deviation from the rational asset prices.

This study analyzes institutional herding at the stock level, but further studies can be conducted at the industry level. Furthermore, the characteristic herding analysis can be detailed by using specific stock characteristics like volume, volatility, book-to-market values, beta etc. The researchers may investigate the relationship between the herding behavior and skill of the institutional portfolio managers as in the study of Jiang & Verardo [97].

The key findings in the analysis of institutional herding in BIST between March 2006 and September 2019 are summarized in this chapter. The herding behavior of domestic institutions is driven by informational cascades, and foreign institutions is driven by both information cascades and investigative herding. The differences of behavior in large-capitalization stocks may be related to informational asymmetries that the institutions are facing. The domestic institutions may have more reliable private own information in large-capitalization stocks and act on this information.

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