HERD BEHAVIOR

IN THE TURKEY STOCK MARKET

EZGİ AKÇAALAN

May 2017

HERD BEHAVIOR

IN THE TURKEY STOCK MARKET

A THESIS SUBMITTED TO

THE GRADUATE SCHOOL OF SOCIAL SCIENCES OF

IZMIR UNIVERSITY OF ECONOMICS

BY

EZGİ AKÇAALAN

IN PARTAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF

MASTER OF ARTS

IN

THE GRADUATE SCHOOL OF SOCIAL SCIENCES

May 2017

Approval of the Graduate School of Social Sciences

Assoc. Prof. Dr. Ö. Osman DEMİRBAŞ

Director

I certify that this thesis satisfies all the requirements as a thesis

For the degree of Master of Arts.

Prof. Dr. Ayla OĞUŞ BİNATLI

Head of Department

This is to certify that we have read this thesis and that in our opinion it
is fully adequate, in scope and quality, as a thesis for the degree of master of Arts.

Prof. Dr. Ayla OĞUŞ BİNATLI

Supervisor

Examining Committee Members
(Title and Name in alphabetical
order of last name)

Prof. Dr. Sacit Hadi AKDEDE

Prof. Dr. Ayla OĞUŞ BİNATLI

Assoc. Prof. Dr. Alper DUMAN

Abstract

HERD BEHAVIOR

IN THE TURKEY STOCK MARKET

AKÇAALAN, EZGİ

May 2017

Master of Arts in Financial Economics, Graduate School of Social Sciences

Supervisor: Prof. Dr. Ayla Oğuş Binatlı

This study examines herd behavior of investors in the Turkey stock market using daily data during the time period from 1991 to 2016. We use three approaches which are cross-sectional dispersion of returns, quantile regression and state-space model for whole market and different market conditions as separated by up and down markets. First, as a result of using cross-sectional dispersion of returns analyses, the existence of herd behavior is found in the market and also in rising and falling markets. Second, by applying quantile regression method, we only find no evidence of herding in the highest quantile region for rising market. Also, when we test the asymmetry of herd behavior, our results show that we can assume investors in Turkey react similarly to good and bad economic news for both up and down markets. Third, with state-space model, the results indicate that herding remains significant and persistent. Moreover, we test causes of herd behavior with Granger Causality test and the results support that the changes of volatility and return of previous days may be an explanation on herd behavior.

Keywords: herd behavior, cross-sectional standard deviation, cross-sectional absolute deviation, quantile regression, state-space model, Granger causality

Özet

TÜRKİYE HİSSE SENEDİ PİYASASINDAKİ

SÜRÜ DAVRANIŞI

AKÇAALAN, EZGİ

Mayıs 2017

Finans Ekonomisi Yüksek Lisans Tezi, Sosyal Bilimler Enstitüsü

Tez Danışmanı: Prof. Dr. Ayla Oğuş Binatlı

Bu çalışma, Türkiye hisse senedi piyasasındaki yatırımcıların sürü davranışlarını, 1991 ile 2016 yılları arasında günlük verileri kullanarak incelemektedir. Tüm hisse senedi piyasasını ve piyasayı azalan ve yükselen piyasalar şeklinde ayrılarak incelemek için getirilerin yatay kesit dağılımı analizi, kantil regresyon analizi ve durum-uzay modeli olmak üzere üç yaklaşım kullandık. İlk olarak uygulanan getirilerin yatay kesit dağılımı metodu ile analizinin sonucunda, yatırımcıların tüm market piyasasında ve ayrıca yükselen ve alçalan piyasa koşullarında sürü davranışı gösterdikleri bulunmuştur. İkinci olarak, kantil regresyon analiz yöntemi ile sürü davranışının sadece yükselen piyasalarda en yüksek kantil alanında görülmediğini bulduk. Ayrıca, sürü davranışının asimetrisini test ettiğimizde, Türkiye'deki yatırımcıların yükselen ve alçalan piyasalardaki iyi ve kötü ekonomik haberlere benzer şekilde tepki verdiklerini gördük. Son olarak, durum-uzay modeli ile de sürü davranışının varlığını anlamlı ve kalıcı bir şekilde devam ettirdiği sonucuna vardık. Bunlara ek olarak, sürü davranışının nedenlerini Granger Nedensellik testi ile araştırdığımızda sonuçlar, bir önceki gün dalgalanma ve getiri değişikliklerin sürü davranışının açıklaması olabileceğini gösterdi.

Acknowledgments

I would like to thank my supervisor Prof. Dr. Ayla Oğuş Binatlı for her support, time and helpful comments. Also, I want to thank Assist. Prof. Dr. Burak Dindaroğlu for his support and his advice to investigate herd behavior. Special thanks must go to Murat Özdemir for his help about some data transporting.

I also want to thank my family and friends for their endless support.

Table of Contents

List of Tables

Table

List of Figures

Figure

Chapter 1. Introduction

When individuals tend to ignore their own private opinions and are influenced by what others around them are doing, this is commonly referred to as herd behavior in the literature. People can exhibit herd behavior in everyday life such as preference of clothes, schools, restaurants or technological gadgets. These influences usually are a signal for herd behavior and so there are lots of studies to investigate herd behavior in the literature.

The herding phenomenon was first investigated in psychology. Solomon Asch (1951) conducted some psychological experiments which are now named Asch Paradigm or Asch conformity experiments in which people suppress their own private signal and rely predominantly on group opinion.[1] In each of these experiments Asch placed a subject member in a group and other members of group were confederates. In a sequence of 18 trials, the group was asked about the lengths of line segments. On the first two trials, both the subject and the confederates gave the correct answer and then, on the third trial the all confederates would give the same wrong answer and wrong responses were repeated 11 times of the remaining 15 trials. Aim of the study was to test how many subjects would change their answer to conform to the confederates, despite it being wrong. The results showed that over thirty percent of subjects gave the wrong answer and conformed to the confederates. Asch's experimental procedures were modified slightly with several variations, and the same results where participants conformed to the majority group, were found in about one to third of all critical trials.

These influences can be in financial markets as well as in everyday life. In financial literature, herd behavior can exist when an investor imitates the observed actions of others or the market movements instead of following his/her own information and beliefs.

Banerjee (1992) gave a common real world example about an individual's choice among two restaurants. He suggested that there were two restaurants A and B which were next to each other and there were 100 people who are faced with a

[1]Asch explored several variations on the paradigm from his study in 1951. It can be seen from the website https://en.wikipedia.org/wiki/Asch_conformity_experiments and the paper of Asch (1955).

choice about the quality of the restaurants. It was known from prior probabilities that restaurant A was better with 51 percent compared to restaurant B. In a sequence, people came at the restaurants and observed the others' restaurant choices. He assumed that each person has a signal of quality which was that either A or B was better, with a probability that the signal could be wrong. Suppose that 99 of these 100 people's signal were about B being better but the one person whose signal was A chose first. Although the second person knew that the first person's preference was A, he/she rationally ignored his/her own signal and chose to go by the prior probabilities and went to A. Then, the third one made the same choice like his/her predecessors and so on. Thus, those who came after suppressed their opinion and joined the herd. If the second person had used his/her own information, this might have encouraged the rest of the population to use their own information. As a result, they all displayed herd behavior.

It is also said that many stock crises have emerged due to investors' psychology, namely herd behavior. De Bondt et al. (2008) said that investment portfolios were mostly distorted and thus stocks and bonds prices would be volatile. So, many researches assumed that investors' psychology had a crucial impact on financial markets and sometimes on stock crises such as the Asian crisis of 1997, the dot-com bubble of 2000s and the financial crisis of 2008. For example, dot-com bubble was a historic economic bubble when there was a rapid rise in equity markets in which NASDAQ index for technology shares traded on Wall Street over the period from 1997 to 2001[2]. After the increasing internet usage, many investors tended to invest in any company which had the internet extensions betting on the future of online trading. For this reason, many Internet-based companies were founded (known as dot-coms) and investors thought that these types of companies would bring in millions. So, most of investors ignored the fundamental rules of investing in the stock market such as studying market trends, reviewing business plans and this behavior lead to overvalue of stocks. Also, when the market was highest values, some high-tech companies (such as Dell and Cisco) sold the majority of their stocks and this cause a panic selling among investors. In a few weeks, the stock market lost its value about 10% and by the end of 2001, most of the traded dot-com companies failed completely and trillions of dollars of investment capital

[2] See more information about bubbles in Shiller (2003)

evaporated. Companies such as Pets.com, Webvan closed completely, others such as Cisco lost with a decrease at 86% but remained stable and profitable some such as Amazon.com were able to recover with smart policies, purchases were made and new products were offered to the market.

Also, herding has been examined in various contexts as theoretical and empirical studies. The theoretical parts of studies on herding focus on the causes and implications of herd behavior. The main consensus of the studies is that herding can be built as being a rational or an irrational form of investor behavior. As said in Devenow and Welch (1996), herding can be irrational when investors blindly follow the others due to some psychological reasons. On the other hand, rational herding view focuses on externalities, the optimal decision making problems in which investors have a reason to believe that they lack information or others are better informed. For example, Scharfstein and Stein (1990) indicate that managers may mimic the others' decision due to concern about their reputation. Also, Bikhchandani and Sharma (2001) said that there are several reasons for rational herding and the most important of these are imperfect information, concern for reputation and compensation structures. In other words, according to Bikhchandani and Sharma (2001), there are three reasons why investors change their own decisions after observing others' decisions. First, investors may think that others know something about the return on the investment. Second, imitation of the decisions of others may be rewarded with the incentives which are supplied by the compensation scheme and terms of employment and this is just valid for money managers who invest for others. The third reason of imitation can arise from individuals' intrinsic preference for conformity. Thus, asset prices may deviate from their fundamental values while following gathered information rather than private information and the assets will be mispriced. This mispricing situation may lead to market inefficiency and financial bubbles.

On the other hand, the empirical studies implement statistical methods to determine herding by two streams as group-wide herding and market-wide herding. For instance, Lakonishok, Shleifer and Vishny (1992) and Grinblatt, Titman and Wermers (1995), Gleason and Lee (2003) focus on certain groups herding like money managers, mutual funds. This type of analysis needs details about trading activities of investors. For example, in the study of Lakonishok, Shleifer and Vishny (1992), number of investors and set of stocks need to be known that because, they measured herding as the average investors tendency to buy or sell particular stocks at the same time. The second stream of empirical analysis focuses market-wide herding such Christie and Huang (1995), Hwang and Salmon (2004), Chiang and Zheng (2010), Seetharam and Britten (2013) and Le and Truong (2014) etc. As well as the theoretical parts of herding, group wide herding and market wide herding can cause mispricing of individual asset and is usually observed through the concept of cross-sectional dispersion of stock returns. If herd behavior exists, the dispersion is expected to decline, and this leads to individual stock returns to gather around the overall market return. Three well known herding measures from this stream of the literature are developed by Christie and Huang (1995), Chang, Cheng and Khorana (2000), Hwang and Salmon (2004).

The existent literature tends to suggest that herd behavior is more likely to occur in emerging markets than in developed markets and Turkey is an emerging market. So, we want to investigate the existence of herd behavior in the Turkey stock market and our expectation is that there is herd behavior. We focus on market wide herding, so we take data of all listed firms in the Turkey stock market BIST. To carry out our study, we follow these three well known approaches mentioned above and in addition to these methods, we also test herd behavior with quantile regression approach. With quantile regression, we can enable to seek herding in different quantile of stock return dispersion, not just extreme tails.

The rest of this study is organized as follows. Chapter 2 presents some information about herd behavior. Chapter 3 discusses the previous research on herding. Chapter 4 shows the methodology used to detect herding and chapter 5 describes data and firms. Chapter 6 discusses the empirical results and chapter 7 concludes.

Chapter 2. Background of Herd Behavior

This chapter's aim is to give an understanding of the concept of herd behavior and gives brief descriptions of herding.

Individuals are generally known to be influenced by others while they make decisions in everywhere such as which restaurants we will prefer or which school we will go. This type of behavior generally refers to herd behavior. Also, Banerjee (1992) describes herd behavior as follows,

"Everyone doing what everyone else is doing, even when their private information suggests doing something quite different."

This phenomenon can be valid for financial markets. In financial markets, herd behavior arises when investors disregard their own beliefs and private information and decide to change their decisions and imitate the investing behavior of other investors. Herd behavior is said to exist when an investor makes an investment decision without knowing other's decisions but changes his/her idea to not making that investment when he/she finds other's decision is not to invest. Alternatively, herd behavior occurs if investor changes his/her decision from not to invest to making the investment, when the knowledge is that other investors make the investment.

Moreover, herd behavior can usually be separated into two as rational herd behavior and irrational herd behavior. Rational herding means that investors ignore their information and mimic the others' decision. Irrational herding on the other hand is a situation that investors blindly follow the others and make similar decisions.

2.1. Rational Herd Behavior

There are several potential reasons for rational herd behavior in financial markets. The most important of these are imperfect information, concern for reputation and compensation structures (Bikhchandani and Sharma, 2001).

2.1.1. Information Based Herding and Cascades

First reason of rational herding imperfect information is also known as informational cascades. Individuals can follow each other's decision while they do not know the others' private information. Even though individuals share their private information to each other, the idea of "actions speak louder than words" provides an excuse for herding. If individuals have some opinion about the proper process of actions, inferences about the others' private information can be made from their actions. Then, herd behavior may arise like this setting. However, such behavior is fragile that they may break easily with a little new information. Also, it is idiosyncratic which means that the first few random players determine the type of behavior.

Bikhchandani and Sharma (2001) exhibit an example about how an informational cascade may form. They offer that there are 100 investors and each of them have own assessments and they make decision whether to invest in an emerging market will be profitable or not. The authors assume that 20 investors think that this investment is worth whereas 80 investors believe it is profitable. Each investor just knows their own estimate of the profitability of this investment but they do not know about the others. If these investors discuss their knowledge with each other, they would decide that investing in emerging market is not a good idea. However, they do not share their information with each other and these 100 investors do not make their investment decisions at the same time. Suppose that, the first few investors are these 20 optimistic investors and their decision is to enter the emerging market. Then, this may cause several of the 80 pessimistic investors who think that it is not a good investment to revise their beliefs and decide to invest. As a result, most of 100 investors are influenced by each other and may choose to take part in bad investment decision. Later, when the unprofitability of this investment expose, these investors exit the market. Briefly, people may form their beliefs by observing the behavior or opinions of others.

2.1.2. Reputation Based Herding

If there is uncertainty about the ability or skill of a manager, reputation or career concerns arise. If an employer is not certain or does not have knowledge about the investment manager's ability to make the right choice, then the best for the investment manager is conform with the other investment professionals' decisions. Thus, the investment manager whose skills are unclear keeps this uncertainty his/her ability to manage the portfolio. Similarly, if there are other managers who are uncertainty about their capabilities, they will imitate each other's decisions and this will cause herd behavior.

2.1.3. Compensation Based Herding

It is expected that money managers herd more often since they have more knowledge than individual investors. However, knowledge is not the only reason that they tend to herd. If investment manager's compensation depends on how their performance compares with the other similar professional managers, this breaks the manager's incentives and lead to imitate the decisions of others. So, herd behavior may occur.

2.2. Irrational Herd Behavior

In financial market, herd behavior is explained as rational behavior which caused by imperfect information, concern for reputation and compensation structures. However, it is also argued that herd behavior can be caused by psychological reasons instead of economic reasons, in other words it can be caused by non-rational behaviors. The non-rational view of herd behavior focuses on investors' psychology and that means investors blindly imitate the others while ignoring all rational analysis (Devenow and Welch (1996)). Moreover, popular claim about the irrationality of security markets emphasize the contagiousness of emotions such as panic or frenzy. It is said that this causes excess volatility, destabilizes markets and makes financial system fragile (Hirshleifer and Teoh (2003)). Assume, in a situation of large stock market decline that investors response instantly and sell their stocks to avoid losses because the other investors do like this. This situation can be example that the investors ignore all rational analysis and react in panic.

Chapter 3. Literature Review

In financial markets, investigating herd behavior is becoming increasingly important. Many studies have been done to identify and measure herding, using theoretical or empirical approaches. While the theoretical studies aim to identify the causes of herd behavior, empirical studies implement statistical tools to capture it.

Theoretical studies on herd behavior start with David S. Scharfstein and Jeremy C. Stein (1990), Abhijit Banerjee (1992), Ivo Welch (1992) and Sushil Bikhchandani, David Hirshleifer and Ivo Welch (1992). These papers do not clarify herd behavior in financial markets but reveal its causes and provide implications, describe the process of decisions to buy or sell a stock in sequence. These researchers base their analysis on Bayesian process and indicate that a small number of agents make their decision with their own information; while others follow, mimicking the decision of prior agents, completely ignoring their own private information.

In contrast, the empirical papers generally explore herding by focusing on two types: group wide herding and market wide herding. For instance, Lakonishok, Shleifer and Vishny (1992) and Grinblatt, Titman and Wermers (1995), Gleason and Lee (2003) focus on instances of group wide, among like money managers, mutual funds and only future markets. As we look at the market wide herding, which includes all stocks in the market, we can see most of the statistical used to analyze herding. This type of herding arises when investors ignore their own information about stock characteristics, and follow the performance of the wider market. Ordinarily, herd behavior is examined on basis of particular country, or emerging markets or developed markets. Most of the results show that herding is more likely to take place in emerging markets than in developed markets. In earlier studies, the concept of cross-sectional dispersion of stock returns is usually employed to examine herding. Then, state-space models are developed to investigate the herding phenomenon. Hence, we use these two common statistical methods in our analysis. In the following sections, we provide a more comprehensive review of theoretical and empirical models of herding.

3.1 Theoretical Studies on Herd Behavior

In this section, we will review the most important theoretical models of herd behavior, starting with the findings of Scharfstein and Stein (1990). Their study was on some forces which cause herd behavior in investment. They assumed two managers, A and B, who invest sequentially. When manager A invested first, manager B ignored his/her own information and was concerned only with manager A. This caused to inefficient herd behavior. They called these correlated prediction errors as “sharing-the-blame” effect. In other words, they concluded that managers might mimic others’ investment decisions to enhance their reputation, and this might cause rational herd behavior.

Another crucial theoretical study was done by Banerjee (1992). Banerjee (1992) set up a sequential decision model where individuals looked at their predecessors’ decisions, although they wanted to act differently. This asymmetric information was rational because they suspected that the predecessors had private information and tried to free-ride on it. Hence, this was called herd behavior and it arose naturally, because actions were constantly copied.

Bikhchandani, Hirshleifer and Welch (1992) (henceforth BHW) aimed to explain social equilibrium, such as fashion, custom, and cultural change, in terms of informational cascades. They indicated situations in which informational cascade occurred if individuals observed the behavior of preceding individuals, regardless of their own information, when it was optimal for an individual.

Another study by Welch (1992) investigated informational cascades in the IPO markets. He developed a cascade pricing model by using Bayesian process, in which investors mimicked the actions of earlier investors while ignoring their private information, potentially causing an informational cascade. As a result, IPOs could be underpriced.

Trueman (1994) set a model where investment analysts were influenced by prior analysts’ recommendations. He suggested that analysts might herd while forecasting because of reputational concerns. According to the author, analysts tent to report earnings forecast similar to prior earnings expectations released by other analysts, even if this forecast was not justified by their information.

Avery and Zemsky (1998) (henceforth AZ) studied herd behavior in financial markets by using BHW model, adding a price mechanism. They showed that informational cascades were impossible in the presence of efficient price mechanism. This meant that new information always could reach the market, and this flow of information led the price to converge at the true value. Also, traders always found it optimal to trade on the difference between their own private information and the commonly available information from the history of trades. Therefore, herd behavior, which caused the mispricing of assets, disappeared in the long run. However, the model might be enhanced by additional dimensions of uncertainty beyond the complex information, such as the effect of a shock on the asset value or the quality of traders' information. In this case, herd behavior could occur, and led to short run mispricing. In addition, such a complex information structure made price bubbles and contrarian behavior becomes possible.

3.2 Empirical Studies on Herd Behavior

Purely empirical studies reviewed in this section are categorized as group-wide herd behavior and market-wide herd behavior. This categorized proceeds as follows. First, here is a discussion of the studies of group wide herding and market wide herding, respectively. Second, these two types of empirical studies are divided into developed and emerging countries.

3.2.1 Group-wide herding

An early example of investigation of group-wide herding by Lakonishok, Shleifer, and Vishny (1992) (henceforth LSV) examined the trading patterns of institutional money managers to understand whether or not those institutions destabilized stock prices. They mentioned two characteristics of the trading: herding, since the money managers buy or sell same stocks simultaneously, and positive-feedback trading, which is the relationship between the money managers' demand for a stock and its past performance. They empirically tested their model using 769 tax-exempt equity funds, managed by 341 different U.S money managers for the first quarter of 1985 and the last quarter of 1989. While LSV herding were measured, money managers were divided equally, such that half of them increased their holding and the other half decreased their holdings or alternatively, while 70% of money managers increased their holdings, the other 30% decreased. If money managers accumulated on the same side of market, it could be concluded that herding occurred. The authors found weak evidence of herding in smaller stocks and stronger evidence of positive-feedback trading. They also found no clear evidence that institutional managers destabilize stock prices.

The other group-wide herding study, by Grinblatt, Titman and Wermers (1995), was an analysis of fund managers' tendency to buy and sell the same stocks at the same time (known as herding), and the relation of such behavior with momentum investment strategies. They used 274 U.S. funds between December 31, 1974 and December 31, 1984. Their results presented low level of herding behavior, similar to Lakonishok, Shleifer and Vishny (1992). Despite weak evidence of herding, they found out 77 % of mutual funds are "momentum investors", who bought stocks that were past winners but did not sell past losers.

Wermers (1999) attempted to measure herd behavior in U.S. mutual funds by applying LSV method, using quarterly holding data over the period 1975-1994. He found high level of herding in small stocks, especially growth oriented funds, but low levels in average stocks.

Wylie (2005) investigated herd behavior of mutual fund managers in the U.K. Using new quarterly data set of portfolio holdings of 268 equity mutual funds for the period January 1986 to December 1993. First, he employed the LSV measure without adjustment for inaccuracy, and his findings were similar to Wermers (1999) in the U.S., that herding was higher for small stocks. After some adjustment for bias in the LSV measure, he found herd behavior in both the largest and the smallest stocks, but little in average stocks.

Moreover, there are several studies on herd behavior exclusively in European futures markets and Exchange Traded Funds (ETFs). Gleason, Lee and Mathur (2003) investigated herd behavior in thirteen commodity futures contracts traded on European futures markets (on three European exchanges; FOX, London Futures and Options Exchange; MATIF, Marche a Terme International De France; ATA, Agricultural Futures Market Amsterdam). By applying the Christie and Huang

(1995) herding model, the results showed that herd behavior did not exist in futures markets, and that individuals who traded in futures markets act on their own beliefs.

Another study by Gleason, Mathur and Peterson (2004) examined herding behavior during periods of extreme market movements using sector Exchange Traded Funds (ETFs) in the U.S. market. Gleason et al. (2004) employed intraday data for ETFs listed on the American Stock Exchange (AMEX) for the period from 1999 to 2002 by estimating the models of Christie and Huang (1995) and of Chang, Cheng and Khorana (2000). They found no evidence of herding during periods of extreme market swings, and indicated only a weak presence of asymmetric market reaction to news during periods of stress for both up and down markets. The rate of increase in the dispersion measures was higher in up markets than in down markets.

A study by Trenca, Pece and Mihut (2015) was an investigation of the occurrence of herd behavior for the institutional and individual investors in the Romanian Stock Market, using daily stock prices between 2003 and 2013. They modified the approach of CCK (2000), adding the delayed value of the dependent variable and the average return of the market in order to neutralize the adverse effects on model estimation generated by multicollinearity property. Although there was no evidence of herd behavior by individual investors, the results indicated some herding behavior by institutional investors.

3.2.2 Market-wide herding

Empirical studies of market wide herding, reveal three well known herding measures, developed respectively by Christie and Huang (1995), Chang, Cheng and Khorana (2000), and Hwang and Salmon (2004). We first discuss these crucial studies, and then we divide the studies as emerging and developed markets.

Christie and Huang (1995) (henceforth referred as CH) examined investment behavior during periods of market stress in the US equity market, using daily and monthly returns from the Center for Research in Securities Prices (CRSP) at the University of Chicago on the period from December 1925 to December 1988. To measure the market effect of herding CH used the cross-sectional standard deviation (CSSD), or dispersion of stock returns, regressed with a constant and two dummy variables designed to capture extreme positive and negative market returns. If the dispersion of returns is found low during periods of market stress, they propose that there is an evidence of herding. Rational asset pricing models (such as the Capital Asset Pricing Model) predict an increase in dispersion during periods of market stress, as individual returns vary in their sensitivity to the market returns. Since cross-sectional volatility of returns was not independent of time series volatility of returns, CH found a higher level of dispersion around the market return during large price movements, providing evidence against herding. As a robustness check, they employed cross-sectional absolute deviation (CSAD), producing similar results.

Another major study is by Chang, Cheng and Khorana (2000) (henceforth CCK), who analyzed herding behavior in different international financial markets (i.e. US, Hong Kong, Japan, Taiwan and South Korea). They used the cross sectional absolute deviation of returns (CSAD) as a measure of dispersion instead of CH's CSSD. They expanded the method of CK along three dimensions. First, CCK incorporated nonlinearity specification into the relationship between the level of equity return dispersion and the overall market return. Describing for herding, they stated that "We expect that return dispersion will decrease (or increase at a decreasing rate) with an increase in market return." If the coefficient of the occurrence of herding behavior is negative and statistically significant, this means herding behavior exists. Second, they examined the both developed and developing financial markets. Third, aimed to identify whether or not herd behavior occur after the liberalization of Asian markets or not. Their data was daily stock price data for the whole population of US firms from the Center for Research in Securities Prices (CRSP) at the University of Chicago for the period 1963-1997, and also daily price and return series for Hong Kong (1981-1998), South Korea (1978-1995), Japan (1976-1995), Taiwan (1976-1995) from the Pacific Basin Capital Markets Research Center (PACAP) of the University of Rhode Island. They concluded that there was no evidence of herding in the US and Hong Kong markets, and only partial evidence in the Japanese market. However, they found significant evidence of herding in South Korea and Taiwan, the two developing markets.

After CH and CCK, a new measure of herding was developed by Hwang and Salmon (2001, 2004, and 2005) (henceforth HS) that looked at the cross sectional dispersion of factor sensitivity of assets relative to a given market, and this new measure could allow one to observe movements in fundamentals. Therefore, they could also analyze market wide herding rather than herding by a group of investors. The measure depended not on the time series volatility of the market returns, but on the variability of individual betas and the measure of herding is simply calculated from these. If herding exists toward the market portfolio, the cross sectional variance of the estimated betas will be lower. So, investors herd around the collective market consensus, as reflected in the market index. While HS estimated the beta of single stocks and the market, they standardized the coefficient of systematic risk by dividing the single estimate by its standard error to reach their measure of herding H (the variance of the standardized beta values). Evidence of herding was indicated by a reduction in the cross sectional dispersion of the beta on the market portfolio. They applied this measure to the U.S., U.K. and South Korean markets over the period from 1990 to 2000 and also they observed herding during the 1997 Asian Crisis and the 1988 Russian Crisis. They concluded that herding occurred toward the market portfolio period of quiets rather than market stress. In the U.S. market, herding occurred toward the market portfolio during a period from 1996 to 1998, and in the U.K. they found herding toward the market portfolio between 1997 and 1998 before the 1988 Russian Crisis. For South Korean market, herding is found during the quiet period before the 1997 Asian Crisis. However, later, the South Korean market did not herd towards the market portfolio.

In their later paper (2004), HS considered that investors may follow the performance of the overall market more than they should in equilibrium, and they may be overreact and become too optimistic or pessimistic compared to the equilibrium risk return relationship. As a result, betas and the expected asset returns may be biased. Therefore, they modeled the cross sectional dispersion of the biased betas in a state space model by using Kalman filter. They used the daily data from 1993 to 2002 for the US and South Korean stock markets, the period cover the 1997 Asian crisis and the 1988 Russian crisis. Their results showed the evidence of herd behavior towards the market in both up and down markets, and indicated that herding was less prevalent during periods of market stress such as the Asian and Russian crises. These crises therefore reduced herding, and helped return markets to equilibrium.

Hwang and Salmon (2005) defined herding as “the behavior of investors in the market who follow the performance of factors such as the market portfolio, sectors, styles, or macroeconomic signals, to buy or sell individual assets at the same time and disregard the long-run risk-return relationship differs from the conventional definition.” In this version, they extended their previous measure by adding a non-parametric method, which can lead to investigate the effects of sentiment on herding. Thus, their new method had two sources, one from cross-sectional herding towards the market portfolio, and the other from sentiment. They used monthly data between 1964 and 2002 for the US stock market, and from 1993 to 2002 for the UK and South Korean stock markets. They found herding toward the market portfolio disappears during the Russian Crises in 1998, in the US and UK markets, and the Asian crisis in 1997 in the South Korean market, as in Hwang and Salmon (2004). They argued that herding occurs when investors when investors were certain of the market direction, regardless of whether it is a bull or a bear market.

As mentioned above, many empirical studies focus on investigating herd behavior by separating as developed and emerging countries and both emerging and developed markets. Some of them are reviewed in next sections.

3.2.2.1. Herding in developed markets

Henker, Henker and Mitsios (2006) considered whether or not herding occurred intraday trading in the Australian equity market using data collected by the Securities Industry Research Centre of Asia-Pacific (SIRCA) from the Stock Exchange Automated Trading System (SEATS) of the Australian Stock Exchange (ASX) for the 200 largest ASX stocks for 2001 and 2002. They used the CH (1995) and CCK (2000) methods, and found no evidence of herding in market-wide or the industry sector.

Saastamoinen (2008) examined herd behavior in the Helsinki Stock Exchange (OMXH) using daily stock closing price from the large capital companies and the general stock price index (OMXHPI) to approximate the returns from an equal weighted market portfolio over the period from 2002 to 2007. His study differed from the initial researches in the choice of methodology; his analysis was built on CCK (2000) but employed quantile regression instead of ordinary least squares and dummy variable models. Herd behavior was considered to occur if dispersion of returns decreases or increases at a decreasing rate, and approaches the market rate of return, which means the nonlinear term, is negative and statistically significant. By setting t = 0.1 and t = 0.25, quantile estimates for the extremely low returns can be obtained. Similarly, setting t = 0.75 or t = 0.90 produces quantile estimates for the extremely high returns. Quantile regression has some advantages for detecting herding in equity markets. To begin with, financial data usually do not have normal distribution; therefore quantile regression can give more accurate estimators when the distribution of errors is not Gaussian. Another advantage related to the distribution, when the market is in stress, herding may not be visible in the extreme tails of return distribution. Quantile regression solves this problem because it estimates the effects on the dependent variable over the entire distribution. The final advantage is that quantile regression is robust to the evidence of outliers, reducing the threat to the reliability of results. His result indicated that dispersion increases in a less than proportional rate with the market return in the lower tail (5% or 1%) of stock returns distribution, and this could be evidence for herding.

Zhou and Anderson (2011) investigated herding behavior in the U.S. equity Real Estate Investment Trust (REIT) market for the period from 1980 to 2010. They followed the approach of CCK and quantile regression. According to their results, herding occurred only in the high quantiles (75% or 90%) of the distribution of return dispersion for the whole period, and stronger evidence for herding was found for bear markets compared to bull markets.

3.2.2.1. Herding in both developed and emerging markets

Chiang and Zheng (2010) investigated the existence of herding behavior in 18 countries, divided into three groups: advanced stock markets (Australia, France, Germany, Hong Kong, Japan, the United Kingdom, and the United States); Latin American markets (Argentina, Brazil, Chile, and Mexico); and Asian markets (China, South Korea, Taiwan, Indonesia, Malaysia, Singapore, and Thailand) during the period 1988 to 2009. The method of CCK (2000) was modified by adding a value of an equally weighted realized return of all indexes. They demonstrated that herding behavior occurred in advanced stock markets except for the US and Asian markets. No evidence of herding was found in Latin American markets. This was the opposite of previous results of CCK (2000) and Demirer and Kutan (2006), who concluded that there is no evidence of herding in developed markets and in Chinese markets. Furthermore, they stated that dispersion of stock returns in the U.S. played as a crucial role in herding activity in the non-U.S. markets. In additional, they noted that herding was triggered by crisis within the county and in the neighbor countries. Thus, they revealed the presence of herding in the U.S. and Latin American Markets (especially Mexico and Argentina) during crisis periods.

Economou, Kostakis and Philippas (2011) searched for evidence of herding in the four south European markets (Portugal, Italy, Greece and Spain, called PIGS) by using all listed firms' daily stocks during the period from 1998 to 2008. Their model was based on the methods of CH and CCK and also employed trading volume and volatility as alternate independent variables. Herd behavior was found in the Greek and Italian markets, while there was no evidence of herding for the Spanish market, and there was mixed evidence for the Portuguese market. Also, they noted that herding effects had important asymmetries between rising and falling markets, high and low trading activity and volatility.

3.2.2.3. Herding in emerging markets

This part comprises the empirical studies of herding in emerging markets. In these markets, we can see that, with some exceptions, emerging markets generally indicate herd behavior.

An empirical study of herding was by Demirer and Kutan (2006), who employed CH (1995), CCK (2000) and Gleason et al. (2003, 2004) methods to examine herd behavior in Chinese markets, including both Shanghai and Shenzhen Stock Exchanges, using daily stock return data period from 1999 to 2002 for 375 stocks. They used these three of these methods because in general all of these methods support rational asset pricing theories, and concluded that herd did not play crucial role in stock returns during periods of market stress. Moreover, they found out herd behavior did not exist in Chinese markets, in which participants made rational investment decisions.

Hachicha, Bouri and Chakroun (2007) developed a new approach, called Dynamic Herding, to examine herd behavior. They tested on the Tunisian stock exchange by using data from BVMT and TUNINDEX indexes over the period from 1999 to 2005. This measure was based on the cross sectional dispersion of beta, Hwang and Salmon (2001, 2004) method, but utilizing a dynamic approach to market volatility which relies on a GARCH (1, 1) model. After applying CH (1995) and CCK (2000) methods, and affirming the absence of herding behavior for Tunisian stock markets, they aimed to find the relation between herding phenomenon and the three principle elements of the markets by using HS method; return, volatility and feedback trading. Their investigation of the relationship between trading volume and herding phenomenon, showed that herding behavior explained the trading volume for BVMT index contrary to the TUNINDEX, where there was no evidence of such relation in the two senses. By looking at the relationship between the herding behavior and volatility, they concluded that the herding phenomenon results in an increase in the market volatility. The relationship between the herding phenomenon and the market return indicated a non-significant causality between the return of the Tunindex and herding phenomenon. The original HS model is far from the reality, however it omitted many factors, such the market microstructure and investor psychology. After their new herding measure was applied, the results identified three components of herding. The first one was related to a constant term, which showed the existence of herding phenomenon whatever the market conditions. This finding was consistent with the reality, which meant that at least one investor imitated the others. The second was the anticipation error of the investors concerning the totality of assets. The third component was that current herding depended on previous herding tendency.

Tan, Chiang, Mason and Nelling (2008) investigated herd behavior in both the Shanghai and Shenzhen markets for A shares, which can be purchased and traded by domestic investors, and B shares which are sold only to foreign institutional investors. They used the approach of Chang, Cheng and Khorana (2000), adding trading volume and volatility to CCK'S model as alternate independent variables. They gathered the data on stock prices, trading volume and earnings per share for all firms listed on the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE) over the period 1994 to 2003. Herd behavior was found in both bull and bear markets, and A share investors in the Shanghai market showed more pronounced herd behavior during periods of rising stock markets, high trading volume and high market volatility, while they found no evidence of asymmetric effects in the herding behavior of B share investors.

Another study by Demirer, Kutan and Chen (2010) used three models, CH (1995), CCK (2000) and HS (2004), to analyze herd behavior in the Taiwanese Stock Market for daily returns of 689 Taiwanese stocks between 1995 and 2006 from the Taiwan Stock Exchange Corporation (TSEC). When they employed the linear model of CH (1995), the results indicated that the absence of herd behavior; however, they found strong evidence of herd in all sectors for the non-linear model of CCK (2000), and the state space model of HS (2004). Moreover, they noted that herding behavior mainly occurred during period of market losses.

Another study with quantile regression method was done by Chiang, Li and Tan (2010) to examine herd behavior in both the Shanghai and Shenzhen markets for A and B shares. A share markets are dominated by individual Chinese investors, and B share markets, are dominated by institutional investors from developed countries. The data was taken from daily stock prices and turnover ratios for all firms listed on the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE) over the period 1996 to 2007. Following the approach of CCK, they found evidence of herding in both the Shanghai and Shenzhen A share markets, but none for B share markets. Then, they further analyzed herding by using a quantile regression model, which was based on stock return dispersions. Estimations were made by using the sample points conditional on a specific quantile. By using a quantile regression procedure, they provided evidence of herding in both A share and B share investors, conditional on the dispersions of returns in the lower quantiles. Also, they noted that, B share investors regularly showed herd behavior in the quantiles from the 10% to 50% levels on days of rising stock market returns. However, while this approach showed a general direction for herding, the model failed to capture the distributional information that explains behavioral changes conditional on a particular market condition.

Lao and Singh (2011) examined herd behavior in the Chinese and Indian stock markets, using CCK (2000) approach proposed by Tan et al. (2008). Data set was procured for the top 300 firms (in terms of market capitalization) in the Shanghai A Share index (SHA), and the top 300 firms from the Bombay Stock

Exchange index (BSE) over the period 1999 to 2009. They chose these indexes as the most representative of China and India. They found that herd behavior occurred in both, but its level depended on market conditions, and also herding was more intense during large market movements. Herd behavior existed during rising market trends in India whereas in the Chinese market, it is greater when the market is decreasing and the trading volume is high. Also, they noted that level of trading volume is unrelated with herd behavior in India.

Pop (2012) investigated of herd behavior towards market index in the Romanian Stock Exchange, using HS beta herding method. She used the weekly data over the period from 2003 to 2012 for 65 stocks listed on the Romanian stock exchange. Beta was used to measure a stock’s sensitivity to the overall market, and to classify mispricing of a stock etc. in finance. However, beta risk was unstable over time for wide spread many markets, therefore specified beta as a conditional time varying series. In addition, the followings were employed: two bivariate GARCH models (Dynamic Conditional Correlation (DCC), and fractionally integrated version of the DCC (FIDCC) GARCH Models), two Kalman filter based approaches, which beta coefficient developed as a random walk and mean reverting process, and two bivariate stochastic volatility models with a normal distribution and t distribution for the excess return shocks. While she employed the volatility models, it could be seen that stochastic volatility approach with a t-student distribution clearly outperforms the GARCH model. DDC GARCH model with a GARCH (0, 1) specification did not perform well in terms of root mean squared error (RMSE), except in one case (RPH stock). In addition, Kalman filter performed better in terms of RMSE, in almost half of the cases considered ranks first and outperforms the stochastic volatility model. After the analysis, she concluded that H had a significant and large value, which meant herding existed towards the market portfolio. Furthermore, during the crisis periods, she observed a fall in herding, and a tendency for investors to become more risk adverse and less willing to follow the market movements.

Another study on herd behavior by Malik and Elahi (2014) on the Karachi Stock Exchange (KSE) in Pakistan used daily data for the period 2003 to 2013. They also analyzed herding under bull and bear market conditions and employed ordinary least square (OLS) of CCK (2000) and quantile regression. Using the method of CCK (2000), they showed that herding existed for the whole sample period, in both bull and bear markets. On the other hand, the results of quantile regression revealed that herd behavior occurred in lower quantiles (10% and 25%) against in upper quantiles (75% and 90%) during the sample period. Under bull and bear market conditions, herding existed in lower quantiles (10% and 25%), and extreme upper quantiles (90 %), but not in median (50%) and the other upper quantiles (75%). These results demonstrate that herding was more likely to occur during extreme market conditions in the Karachi stock exchange (KSE).

Messis and Zapranis (2014) studied the presence of herding and its effect on market volatility in the Athens Stock Exchange over the period 1995 to 2010. They employed the state space model of HS (2004) and four volatility measures: generalized autoregressive conditional heteroscedasticity (GARCH (1, 1)) model, the threshold ARCH (TARCH) model, volatility measure of French *et al.* (1987) which takes into account the autocorrelation in daily returns, and finally, the upside and downside volatility, in order to catch the volatility in up and down market returns, which used the daily market returns in month and days with positive and negative market returns. The findings showed that herding occurred in two different periods, in early 1997 and the first quarter of 2003 period and also, the very early part of 2008 up to the last selected month. When they separated the portfolios by beta size, for high beta portfolio, herding started from early 1997 until the middle of 2004, and for the low beta portfolio, adverse herding occurred from the very beginning of 1995 until 2001. Finally, for the medium beta portfolio, herding occurred from early 1997 until late 1998, and for the whole 2001-2003 period. When they applied the volatility measures, they stated that there was a linear effect of herding on the volatility measures, and it occurred during highly volatile periods.

Maria, Maria and Miruna (2015) investigated herd behavior in ten Central and Eastern Europe stock markets (CEE; Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Slovenia, Poland and Romania) during the global financial crisis at the level of different size ranked portfolios of stocks. They employed the CSAD methodology developed by Chang et al. (2000), using daily stock prices for 384 corporations over the period 2003 to 2013. They identified herd behavior during the crisis in five CEE stock markets: Croatia, Hungary, Latvia, Lithuania and Slovenia. Furthermore, they specified the size of portfolios in which herding was displayed and their result indicated that herd behavior occurred for largest portfolios in Bulgaria, Slovenia and Latvia, and for the medium sized portfolios in Estonia.

Kapusuzoglu (2011) and Solakoglu and Demir (2014) examined herd behavior in Turkey stock market after 2000. However, the current study takes a broader perfective on empirical studies, and covers a larger time period.

Kapusuzoglu (2011) analyzed whether or not herd behavior occurred in the market on the basis of 70 stocks traded on the Istanbul Stock Exchange (ISE) in the National 100 index. Data was obtained from the Istanbul Stock Exchange (ISE) Electronic Data Delivery System and Is Investment covering the period between 2000 and 2010. He employed CH (1995) and CCK (2000) methods and after these analysis, the results indicated the presence of herd behavior in the ISE National 100 index on both rising and falling days.

The analysis of herd behavior in the Turkey Stock Market was also studied by Solakoglu and Demir (2014). They examined sentiment herding of investors, which was separated as BIST30 and Second National Market (SNM) in Borsa Istanbul in the aftermath of the country's financial crisis in 2000. The data set was obtained from Matriks Data Terminal over the period between 2000 and 2013. They expected to see evidence of herding by the SNM investors, despite no evidence by BIST30. To analyze sentiment herding, they followed beta herding measure of Hwang and Salmon (2004). As they expect, they concluded that there is no presence of herding in BIST30, but contrary SNM investors exhibited herding in three stages. In the first stage (2000-2004), they saw evidence of herding which was explained by the financial crisis and lack of confidence towards the government. The second stage (2005-2008) was a more stable period, without herding. Finally, in third stage (2009-2013), there was a volatile adverse herding, and investors preferred fundamental values of firms instead of following the market sentiment, because of events such as the constitutional court action against the government, and the mortgage crisis.

Chapter 4. Methodology

In this section, we mention some methods for investigating herd behavior. We begin with two common methods which are proposed by Christie and Huang (1995) (hereafter CH) and Chang et al. (2000) (hereafter CCK). Then, we employ quantile regression on CCK method like Tan at al. (2010). Eventually, state-space model which is developed by Hwang and Salmon (2004) is used. In addition, the analysis is consolidated to find causes and effects of herd behavior by Granger Causality Test.

4.1. Christie and Huang (1995) Approach

One of the earliest studies that determine empirically herd behavior in the financial markets comes from CH. They develop an empirical measure to detect herd behavior by using cross-sectional standard deviation of returns ($CSSD_t$) to represent return dispersion. $CSSD_t$ is calculated by following equation:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}\left(R_{i,t} - R_{m,i}\right)^2}{(N-1)}} \tag{4.1}$$

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

CH suggest that investors make their investment decisions by looking at overall market conditions. During normal periods, rational asset pricing models predict that return dispersion will increase with the absolute value of the market return while investors trade based on their own private information. However, during periods of extreme market movements, the return dispersion will decrease since investors tend to ignore their own belief and follow the market consensus. As a result, stock results will cluster around and not deviate too far from the overall market return. So, CH argue that herd behavior is more apparent under the periods of market stress and lead to lower return dispersion than average.

CH use the following equation to examine herding in their empirical specification:

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t \quad (4.2)$$

$$CSAD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t \quad (4.3)$$

where D_t^L equals 1 if the market return on day *t* lies in the extreme lower tail of return distribution otherwise D_t^L equals zero. Similarly, D_t^U equals 1 if the market return on day *t* lies in the extreme upper tail of return distribution, otherwise D_t^U equals zero. CH employ absolute mean to test robustness of the analysis. CH use the 1% and 5% criterion to determine the upper and lower tail of the market return distribution to define extreme price movement days. If the coefficients β_1 and β_2 are negative and statistically significant, it means herd behavior occurs. In other words, while herd behavior exists in the market, the cross-sectional dispersion of the stock returns will be low under large price movements. In fact, investors' opinion may be different on what constitutes extreme return and the CH method can measure herding only while the market is under stress. It ignores that herd behavior can exist during normal periods as in Hwang and Salmon (2004).

4.2. Chang, Cheng and Khorana (2000) Approach

Chang at al. (2000) extend the CH method by using cross-sectional absolute deviation of returns $CSAD_t$ as a measure of dispersion instead of cross-sectional standard deviation of returns ($CSSD_t$). $CSAD_t$ is defined as follow:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,i}\right| \quad (4.4)$$

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

CCK also state that rational asset pricing models not only predict the relationship between return dispersion and market return as an increasing function, but it is also linear. If investors tend to follow market behavior despite their own priors during periods of large price swings which means herd behavior is present in the market, such a linear and increasing relation between return dispersion and market return will no longer hold. So, herd behavior leads to cause a nonlinear relationship. Because of this, a nonlinear market return should enter in the equation and the relation will no longer be linearly increasing or decreasing. In other words, returns dispersion will decrease (or increase at a decreasing rate) with an increase in the market return if there is herd behavior. They build their model on this intuition and set up a new equation to test for herding:

$$CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{4.5}$$

where $CSAD_t$ is the cross-sectional absolute deviation of stock returns at time *t* and $R_{m,t}$ represents the cross-sectional average of N returns in the market portfolio at time *t*. Furthermore, a statistically significant and negative coefficient γ_2 will be an indicator of herd behavior in the stock market.

They separate the regression model in two as up and down markets to find whether there is any asymmetric herding or not.

$$CSAD_t^{Up} = \gamma_0 + \gamma_1^{Up} |R_{m,t}^{Up}| + \gamma_2^{Up} (R_{m,t}^{Up})^2 + \varepsilon_t \tag{4.6}$$

$$CSAD_t^{Down} = \gamma_0 + \gamma_1^{Down} |R_{m,t}^{Down}| + \gamma_2^{Down} (R_{m,t}^{Down})^2 + \varepsilon_t \tag{4.7}$$

where $|R_{m,t}^{Up}| [|R_{m,t}^{Down}|]$ is the absolute value of an equally weighted return of all available securities on day *t* when the market is up [down] and $(R_{m,t}^{Up})^2 \left[(R_{m,t}^{Down})^2\right]$ is the squared value of this term. If γ_2^{Up} (γ_2^{Down}) is significantly negative, herd behavior exists in the up market (the down market).

Note that, Eq. (4.4) restricts γ_1 to be same for both up and down market which means there is no consideration about asymmetry. To capture this asymmetry, Eq. (4.4) can be alternatively written as in Tan et. Al. (2010):

$$CSAD_t = \gamma_0 + \gamma_1 (1 - D) R_{m,t} + \gamma_2 D R_{m,t} + \gamma_3 R_{m,t}^2 + \varepsilon_t \tag{4.8}$$

where D is a dummy variable which equals 1 when $R_{m,t} < 0$ and D equals to zero otherwise, $R_{m,t}$ is the equally weighted market portfolio return at time *t*. As we mentioned earlier, the coefficient of nonlinearity γ_3 would be negative and statistically significant if herd behavior occurs.

In addition, while Eq. (4.7) is generalized in the following expression, we can see whether herd behavior is asymmetric or not on days when market is up or vice versa:

$$CSAD_t = \gamma_0 + \gamma_1(1-D)R_{m,t} + \gamma_2 DR_{m,t} + \gamma_3(1-D)R_{m,t}^2 + \gamma_4 DR_{m,t}^2 + \varepsilon_t \quad (4.9)$$

where D is a dummy variable which equals 1 when $R_{m,t} < 0$ and D equals to zero otherwise, $R_{m,t}$ is the equally weighted market portfolio return at time *t*.

In Eq. (4.8), if the estimated coefficient γ_3 is significantly negative, we can say there is herd behavior in the up market. Similarly, if the estimated coefficient γ_4 is statistically significant and negative, it means that investors herd in the down market. Briefly, these alternative equations enable us to examine herding and also demonstrate the asymmetric characteristics of returns (see, e.g. Tan et al. 2010; Zhou and Anderson 2011).

Moreover, we test the equality of herding coefficient between up and down markets by the Wald test. Our hypotheses are:

$$H_0: \gamma_3 = \gamma_4$$
$$H_1: \gamma_3 \neq \gamma_4$$

The null hypothesis means investors tend to behave similarly in up and down markets. The alternative hypothesis means investors react differently to up and down markets. If the p value of the null hypothesis is larger than significance level, we cannot reject the null hypothesis which means investors in Turkey respond to good and bad economic news symmetrically for both the up and down markets.

4.3. Quantile Regression Approach

While some researchers employ ordinary least square regression to detect herding, some decide to use quantile regression (QR) (Koenker and Bassett 1978). This approach enables one to seek herding in different quantile of stock return dispersion, not just extreme tails. Besides, it solves some statistical problems such as non-normal distributions, errors invariables, omitted variables bias, sensitivity to outliers (Koenker 2005; Barnes and Hughes 2002).

To solve these issues, conditional quantile regression function can be written as:

$$Q_{y_i}(\tau|x_i) = x_i'\gamma \tag{4.10}$$

where y_i is the dependent variable and x_i' is a vector of independent variables and γ is a vector of coefficients. If we do minimizing weighted deviations from the conditional quantile, we get:

$$\widehat{\gamma_\tau} = \arg\min \sum_{i=1}^{n} \rho_\tau\,(u_i) \tag{4.11}$$

where $u_i = y_i - x_i'\gamma$,$y_i$is the conditional distribution of the dependent variable which characterized by different values of the τth quantile given x_i (Koenker, 2005), and ρ_τ is a weighting factor. For any $\tau \in (0,1)$, weighting factor is defined as:

$$\rho_\tau(u_i) = \begin{cases} \tau u_i & if\ u_i \geq 0 \\ (\tau - 1)u_i & if\ u_i < 0 \end{cases} \tag{4.12}$$

Then, the coefficients of quantile regression estimatorsγ_τ for a given τ are estimated by minimizing the weighted sum of absolute errors as follows:

$$\widehat{\gamma_\tau} = \arg\min \left(\sum_{i:y_i > x_i'\gamma} \tau|y_i - x_i'\gamma| + \sum_{i:y_i > x_i'\gamma} (1-\tau)|y_i - x_i'\gamma| \right) \tag{4.13}$$

Therefore, quantile regression allows us to investigate the relationship between $CSAD_t$ and $R_{m,t}^2$ at any specific quantile. So, quantile regressions for $CSAD_t$ and $R_{m,t}^2$ for τ quantiles are characterized as:

$$Q_r(\tau|X_t) = \gamma_{0,\tau} + \gamma_{1,\tau}\left|R_{m,t}\right| + \gamma_{2,\tau}R_{m,t}^2 + \varepsilon_{\tau,t} \tag{4.14}$$

$$Q_r(\tau|X_t) = \gamma_{0,\tau} + \gamma_{1,\tau}(1-D)R_{m,t} + \gamma_{2,\tau}DR_{m,t} + \gamma_{3,\tau}(1-D)R_{m,t}^2 + \gamma_{4,\tau}DR_{m,t}^2 + \varepsilon_{\tau,t} \tag{4.15}$$

where $CSAD_t$ is the cross-sectional absolute deviations of returns which is dependent variable and $R_{m,t}$ is the equally weighted market portfolio return at time *t*. X_t represents a vector of right-hand-side variables on the above equation. $\gamma_{k,\tau}$ refers to the kth coefficient conditional on τth quantile distribution in the estimated equation. Eq. (4.14) represents the regression for the market and eq. (4.15) indicates the regression for the up and down markets.

Like the earlier analyses, the negative and statistically significant coefficient of the nonlinear term is an indicator of herd behavior. In addition, the Wald test is used to test the equality of herding coefficient as before to capture asymmetry.

4.4. Hwang and Salmon (2004) Approach

Hwang and Salmon (2004) develop a new approach that looks at the cross sectional dispersion of factor sensitivity of assets relative to a given market and this new measure can give a chance to observe deviations from equilibrium beliefs expressed in CAPM. The measure does not depend on the time series volatility of the market returns but depends on the variability of individual betas and the measure of herding is simply calculated from the individual betas. If herding exists toward the market portfolio, the cross sectional variance of the estimated betas will be lower. So that investors herd around the collective market consensus as reflected in the market index. While they estimate the beta of single stocks and the market, they standardize the coefficient of systematic risk by dividing the single estimate by its standard error. After all, they reach their measure of herding H (the variance of the standardized beta values) and evidence of herding is indicated by a reduction in this quantity. If the value of H increases and any significant deviation of the coefficient from zero, it represents herding.

Before to test herding, they consider the following CAPM in equilibrium,

$$E_t(r_{it}) = \beta_{imt} E_t(r_{mt}) \tag{4.16}$$

where r_{it} and r_{mt} are the excess returns of asset *i* and market at time *t*, β_{imt} is the systematic risk measure and $E_t(.)$ is conditional expectation at time *t*.

The conventional CAPM assumes that β_{imt} does not change over time and estimates stock price given the value of systematic risk (β_{imt}) and expected market excess returns $E_t(r_{it})$. However, Hwang and Salmon (2004) assume that the investor sees the market as a whole and consider the value of individual stocks. Thus, if herding occurs in the market, equilibrium betas or expected stock returns may change over time and be biased, at least in the short run. So, they use an alternative equation to measure herding instead of using the equilibrium CAPM:

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1) \tag{4.17}$$

where $E_t^b(r_{it})$ and β_{imt}^b are the market's biased short run conditional expectation on the excess returns of asset *i* and its beta at time *t*, $E_t(r_{mt})$ is the excess returns of the market at time *t* and h_{mt} is a herding parameter that changes over time, $h_{mt} \leq 1$, and conditional on market fundamentals.

- When $h_{mt} = 0$ and $\beta_{imt}^b = \beta_{imt}$, there is no herding and the equilibrium CAPM holds.
- When $h_{mt} = 1$, we have $\beta_{imt}^b = 1$ which means that the beta on the market portfolio and the expected excess return on the individual asset will be equal. So, $h_{mt} = 1$ means there is a perfect herding towards the market portfolio and all the individual stocks move in the direction and with same magnitude as the market portfolio.
- When $0 < h_{mt} < 1$, there is some degree of herding and it is determined by the value of h_{mt}. In this situation, we have $\beta_{imt}^b < \beta_{imt}$ for an equity for which $\beta_{imt} > 1$ and $E_t(r_{it}) > E_t(r_{mt})$, the equity will herd towards the market and biased expected returns move closer to expected market return and the relationship between true and biased expected excess returns is $E_t(r_{it}) > E_t^b(r_{mt})$. Because of this, the equity seems less risky than it should be. In other respects, if we have for equity $\beta_{imt} < 1$ and $E_t(r_{it}) < E_t(r_{mt})$, the equity will herd towards the market when biased expected returns moves closer to expected market return so that the relationship will be seen like $E_t(r_{it}) < E_t^b(r_{it}) < E_t(r_{mt})$. In this situation, the equity looks riskier than it should be.

- When $h_{mt} < 0$, there is reversed herding. In this case, when $\beta_{imt} > 1$, betas become higher as $E_t^b(r_{it}) > E_t(r_{it}) > E_t(r_{mt})$ and on the contrary when $\beta_{imt} < 1$, betas become lower as $E_t^b(r_{it}) < E_t(r_{it}) < E_t(r_{mt})$.

Using the relation described in Eq. (4.17), we can estimate the herding for all assets in the market portfolio rather than a single asset. Hereby, the effect of idiosyncratic movements of individual betas β_{imt}^b will be removed. So, to measure h_{mt}, cross-sectional dispersion of biased betas (β_{imt}^b) is calculated as follows:

$$Std_c(\beta_{imt}^b) = Std_c(\beta_{imt})(1 - h_{mt}) \tag{4.18}$$

where $Std_c(.)$ represents the cross standard deviation.

While the effect of idiosyncratic changes in β_{imt} is minimized by estimating the cross-sectional standard deviation of betas $Std_c(\beta_{imt})$ for all assets in the market, $Std_c(\beta_{imt})$ is allowed to be stochastic in nature. However, $Std_c(\beta_{imt}^b)$ is not expected to change significantly in the short run if the structure of companies within the market won't reveal dramatic changes. Therefore, changes in $Std_c(\beta_{imt}^b)$ over a short time interval can be attributed to changes in herding parameter h_{mt}.

Taking logarithm of Eq. (4.18), it is procured:

$$log[Std_c(\beta_{imt}^b)] = log[Std_c(\beta_{imt})] + log[1 - h_{mt}] \tag{4.19}$$

Using the assumption on $Std_c(\beta_{imt})$, above equation can be written:

$$log[Std_c(\beta_{imt}^b)] = \mu_m + \upsilon_{mt} \tag{4.20}$$

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

$$log[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + \upsilon_{mt} \tag{4.21}$$

where $H_{mt} = (1 - h_{mt})$. Thereby, H_{mt} is allowed to evolve over time and followed a dynamic process; for example if a mean zero AR (1) process is assumed, state-space model is characterize as:

$$log[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + \upsilon_{mt} \tag{4.22}$$

$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt} \tag{4.23}$$

where $\eta_{mt} \sim iid\ (0, \sigma^2_{m\eta})$. This is now a standard state-space model which can be estimated by the Kalman filter. H_{mt} is the state equation and when $\sigma^2_{m\eta}$ has a significant value, it means herding exist and a significant ϕ_m support this particular autoregressive process.

As mentioned above, $log[Std_c(\beta^b_{imt})]$ is expected to change over time in return for the level of herding in the market. However, to check robustness of herd behavior extracted from $Std_c(\beta^b_{imt})$, we include market volatility and market returns as potential variables that reflect macroeconomic fundamentals. If H_{mt} becomes insignificant after including these two variables, we can conclude that changes in $Std_c(\beta^b_{imt})$ is interpreted by these fundamentals rather than herding.

Thus, when two exogenous variables are considered as independent variables, we have the following model:

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + c_{m1} log\sigma_{mt} + c_{m2} r_{mt} + v_{mt} \qquad (4.24)$$

$$H_{mt} = \varphi_m H_{mt-1} + \eta_{mt} \qquad (4.23)$$

where $log\sigma_{mt}$ is market log volatility and r_{mt} is market return at time t.[3]

4.4.1. Estimating the Cross-Sectional Standard deviation of the Betas

According to Hwang and Salmon (2004) model, the capital asset pricing model (CAPM) betas of individual assets will be biased away from their equilibrium when investors herd toward the market portfolio. Hence, we need to estimate the betas and calculate cross-sectional standard deviation of the betas to be used in state space models. To reduce estimation error in the beta estimates, we use 1-month's data at a time to estimate the betas like Hwang and Salmon (2004). Therefore, the betas are calculated with daily data over monthly intervals by using standard ordinary least squares (OLS) as in following equation;

$$r_{it_d} = \alpha^b_{it} + \beta^b_{imt} r_{im_d} + \varepsilon_{it_d} \qquad (4.25)$$

[3]The monthly market volatility is calculated by using square daily returns as in Schwert (1989).

Where r_{it_d} represents to daily excess return of stock i, r_{im_d} refers the daily excess returns of the market for the month *t*. In other words, the subscript t_d denotes daily data *d* for the given month *t*. Excess returns are calculated with 3 month Treasury bill for Turkey. Then, with these estimated betas, a monthly time series is created by calculating the cross-sectional standard deviations of the betas. Also, after estimation of betas, the cross-sectional standard deviation of the monthly betas is obtained as following;

$$Std_c(\beta_{imt}^b) = \sqrt{\frac{\sum_{i=1}^{N_t}\left(\beta_{imt}^b - \overline{\beta_{imt}^b}\right)^2}{N_t}} \tag{4.26}$$

where $\overline{\beta_{imt}^b} = \frac{1}{N_t}\sum_{i=1}^{N_t}\beta_{imt}^b$ and N_t is the number of equities in the month *t*.

Moreover, to test normality of distributions, Jarque-Bera statistic is employed as follow;

$$JB = n\left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right] \tag{4.27}$$

$$\alpha = 0.05 \quad \chi^2(2) = 5.991$$

where n represents sample size, S is skewness and K is kurtosis. The hypotheses are:

$$H_0 = Series\ are\ normally\ distibuted.$$

$$H_1 = Series\ are\ not\ normally\ distibuted.$$

If JB is greater than the value of $\chi_{\alpha,df}^2$, null hypothesis of normality is rejected.

4.5. Granger Causality Test

In order to highlight the robustness, we examine the relationship between the herd behavior and some elements of the market such as market volatility, market return and β as market direction. To investigate the cause and effects of herding, we use Granger Causality Test (Granger, C. 1969). Granger causality analysis is usually performed by fitting a vector autoregressive model (VAR) to the time series. The VAR model is expressed by the following equation:

$$y_t = \alpha + \sum_{i=1}^{d} \phi_i y_{t-i} + \varepsilon_t \tag{4.28}$$

where y_t is a vector of the dependent variables, ϕ_i is matrix of autoregressive coefficients, d is number of lagged and ε_t is vector of error terms. For the lag selection order, AIC and SIC which are more common, are used. Also, the hypotheses of Granger causality are:

$$H_0 = lagged\ x\ values\ do\ not\ cause\ the\ variation\ in\ y$$

$$H_1 = lagged\ x\ values\ do\ cause\ the\ variation\ in\ y$$

If the p value < significance level, we can conclude that causality sense is significant.

This section, we refer the methods which we use to detect market wide herding in Turkey. In addition, while applying these four pioneering models, we want to present an extensive perspective to herd behavior in Turkey. The next section is about the data which we use to perform these methods.

Chapter 5. Data

In this section, the data which we employ in this study is described. In addition, some descriptive statistics are presented about the data and firms.

All data employed in this study is collected from Matrix Data Terminal for the Turkey Stock Market BIST.[4] We collect daily stock prices for all listed 499 firms on the BIST over the period 2 January 1991 to 6 may 2016. The whole data period covers 1,683,922 daily closing prices. We use Stata 12 to do our analyses. The returns for individual stocks are calculated as;

$$R_t = \frac{ln(P_t)}{ln(P_{t-1})}$$

where P_t is the closing price of a stock at time *t* and P_{t-1} previous close price of a stock at time *t*.

When we examine all listed 499 stocks on the BIST, it can be seen although there are only 5 stock in 1991, 437 stocks are listed in 2016.[5] Two of these 5 stocks are traded still in 2016 and both stocks belong to Turkey Is Bank (ISATR and ISBTR). Also, when we investigate the number of stocks per a year, we can see that number of traded stocks has increased over the years and Fig. 1 display clearly this rising.[6]

Moreover, Turkey Is Bank (ISBTR), Ihlas Madencilik AS (IHMAD) and Boyner Perakende ve ekstil Yatirimlari AS (BOYP) have largest number of traded stock and these numbers of traded stocks are respectively 5,988, 5,988 and 5,985. Iskenderun Demir ve Celik AS (ISDMR) have the smallest number of traded stock which have only 25 observations. Stocks of Iskenderun Demir ve Celik started to be traded in 2016 and exit the Turkey stock market in 2016. That is why it is the smallest stocks traded in the market. Besides, the time path of traded stocks can be seen from Figure 2.[7]

[4]Matrix Data Terminal provides the real data for the all stocks which are listed in the stock market. We get demo version to obtain daily closing prices from https://store.matriksdata.com
[5]Descriptive statistics of 499 stock returns' observations are in Appendix A, Table A1.
[6]Number of all listed stocks by years can be seen in Appendix A, TableA2.
[7] Total number of stocks by years can be seen in Appendix A, Table A3.

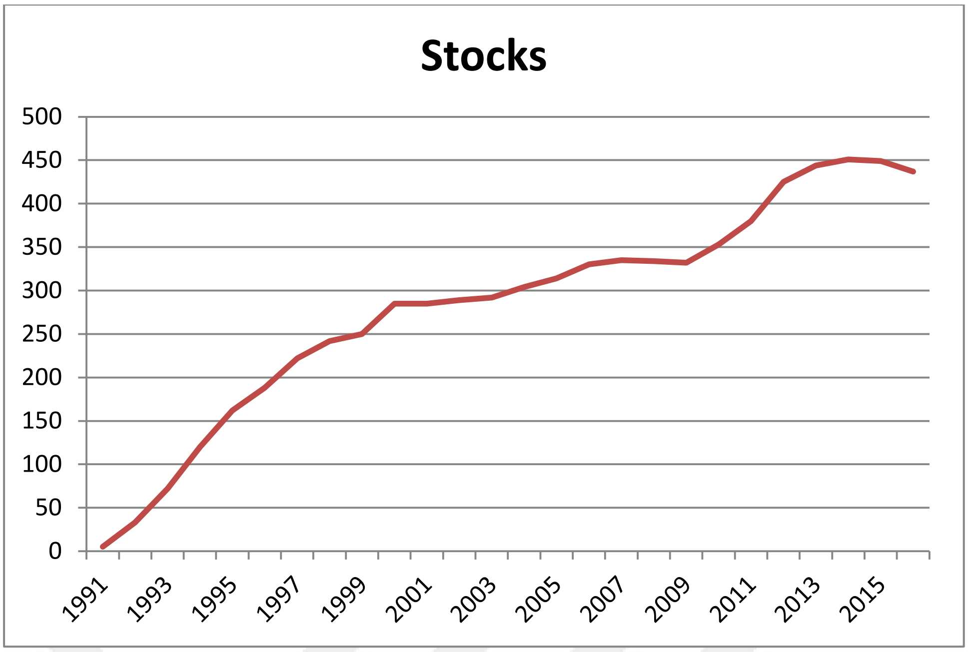

Figure 1.Time path of the number of all listed stocks per a year

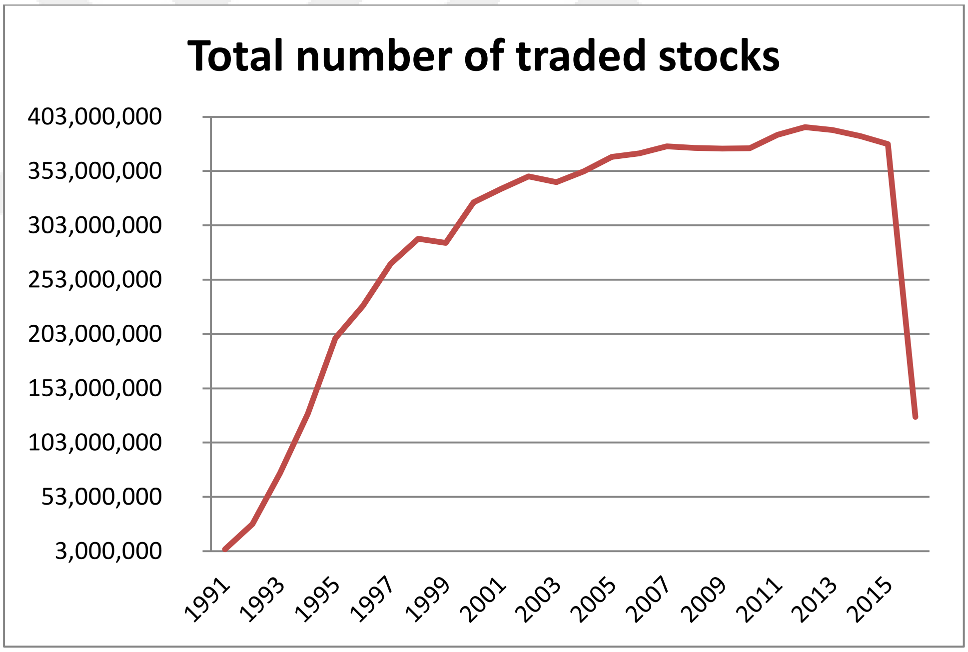

Figure 2.Time path of traded stocks

While we determine existence of herd behavior, we use two approaches as regressions and state-space model (as mentioned the next sections). Therefore, we need to do some transformations on our data sample. First, we need cross-sectional dispersion of stock returns at time *t* to run regressions. When we utilize cross-sectional transformation, we obtain 6,340 observations to analyze.

Furthermore, when we examine data, it can be clearly seen that total number of stocks and traded stocks per year has increased since 2000. So, to check robustness of herding, we repeated the cross-sectional analyses after 2000 and then 1,393,346 daily data remain. When we did cross-sectional transformation, 4,100 observations are obtained to run regressions. [8]

Second step for our study is about state-space model which we need a monthly time series. A total number of 1,326,848 daily data from 2 January 2001 to 29 April 2016 is used. For each month, daily returns of the month are used to estimate betas of each stock and they are used to calculate cross-sectional standard deviation of betas of the month. After running ordinary least square, we get 68,461 betas. We take betas that are computed with 17 and more observations for each month to calculate the cross-sectional standard deviations. The only exceptions are February, 2003 and November, 2003, for which we allow 15 and 13 observations in these months respectively, in order to obtain a sufficient number of observations and then 63,106 betas remain to analyze. Eventually, after this procedure, we obtain a total number of 184 monthly cross-sectional standard deviation of betas.

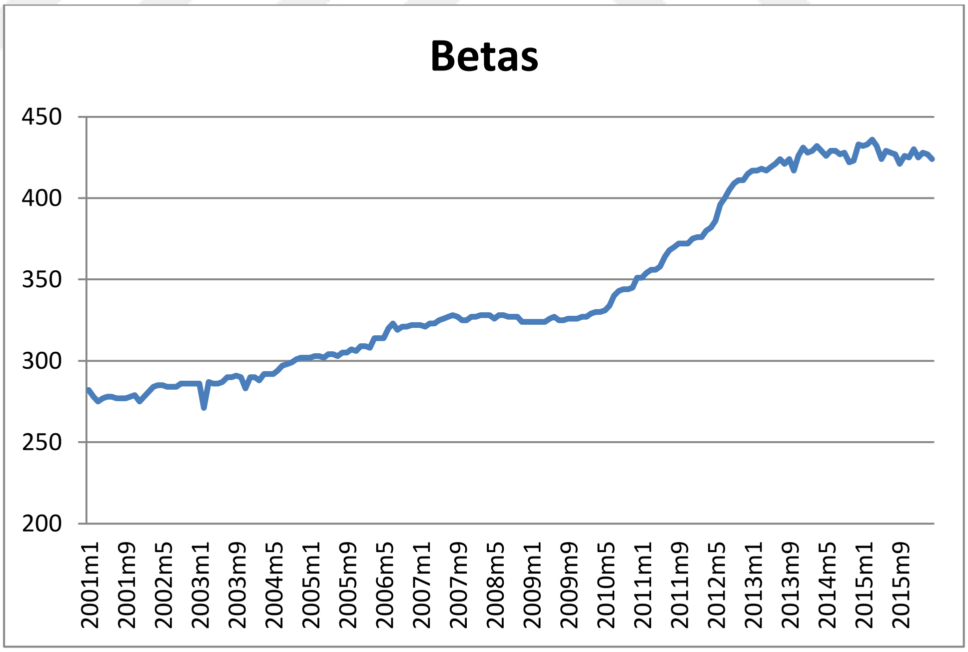

Figure 3.The time path of betas for each month

[8] Descriptive statistics of 499 stock returns' observations after 2000 are in Appendix A, Table A4.

When we calculate monthly time series, there are more than 271 betas in each month. The month which has minimum number of betas is February 2003 with 271 observations and the month which has the maximum number of betas is March, 2015 with 436 observations. The average of betas is 342.967 and the month that has smallest beta which is -3.464, is February 2016 with 428 observations. On the other hand, the largest beta is 11.897 in October 2004 with 301 observations.[9] Moreover, Fig. 3. shows the time path of betas according to the months.

[9] Descriptive statistics of betas by months are in Appendix A, Table A5.

Chapter 6. Empirical results

In this section, some econometric techniques are used to investigate herd behavior in Turkey Stock Market, namely ordinary least squares, quantile regression, state-space and granger causality. We analyze 1,683,922 daily closing prices and that are obtained from the Matrix Data Terminal for the period 2 January 1991 to 6 may 2016.

6.1. Descriptive Statistics

Our first step is to calculate cross-sectional standard deviations and cross-sectional absolute deviations which are expressed as;

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}\left(R_{i,t} - R_{m,i}\right)^2}{(N-1)}} \tag{4.1}$$

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,i}\right| \tag{4.3}$$

where N is the number of firms in the portfolio, $R_{i,t}$ is the daily return of the stock of firm *i* at time *t* and $R_{m,i}$ is the cross-sectional average return of N stocks in the market portfolio at time *t*.

Table 1. Descriptive statistics of market return, cross-sectional standard deviation and cross-sectional absolute deviation

Variable	Mean	S.D.	Min	Max	ADF Test
$R_{m,t}$	0.0010	0.0242	-0.2310	0.2310	(-74.520)***
$CSSD_t$	0.0281	0.0163	0.0000	0.3196	(-40.705)***
$CSAD_t$	0.0117	0.0052	0.0000	0.0412	(-28.454)***

Table 1 contains summary statistics for market return, cross-sectional standard deviation and cross-sectional absolute deviation. S.D. represents standard deviation and ADF Test represents Augmented Dickey Fuller Test. After calculating

$R_{m,t}$, $CSSD_t$ and $CSAD_t$ and remove duplicate dates, there are 6340 remaining observations to analyze. The statistics show us the average of $CSSD_t$ is higher than $CSAD_t$ and the average of $R_{m,t}$ is around zero. The highest and lowest values of market return are 0.231 and -0.231 which are respectively 04/02/1991 and 05/02/1991 and its standard deviation is not too much. Moreover, the unit root (ADF) tests indicate that all series are stationary.

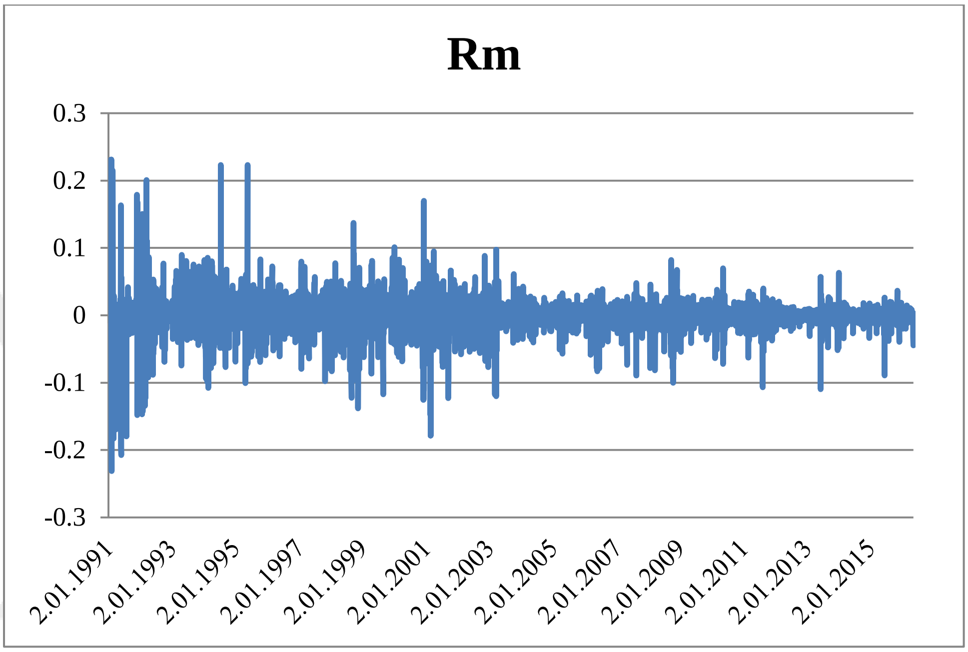

Figure 4.Plot displaying daily return of all securities in BIST

The Figure 4 shows us how daily returns have changed throughout the period 02.01.1991 and 06.05.2015 consisting of 24 years in total. From the graph volatility clustering is evident, as some periods show high volatility while others show low volatility. Particularly, before first period of 2003 market return has more widely volatile and sharp spikes. After 2004, the market becomes more stable although it has some rises and falls.

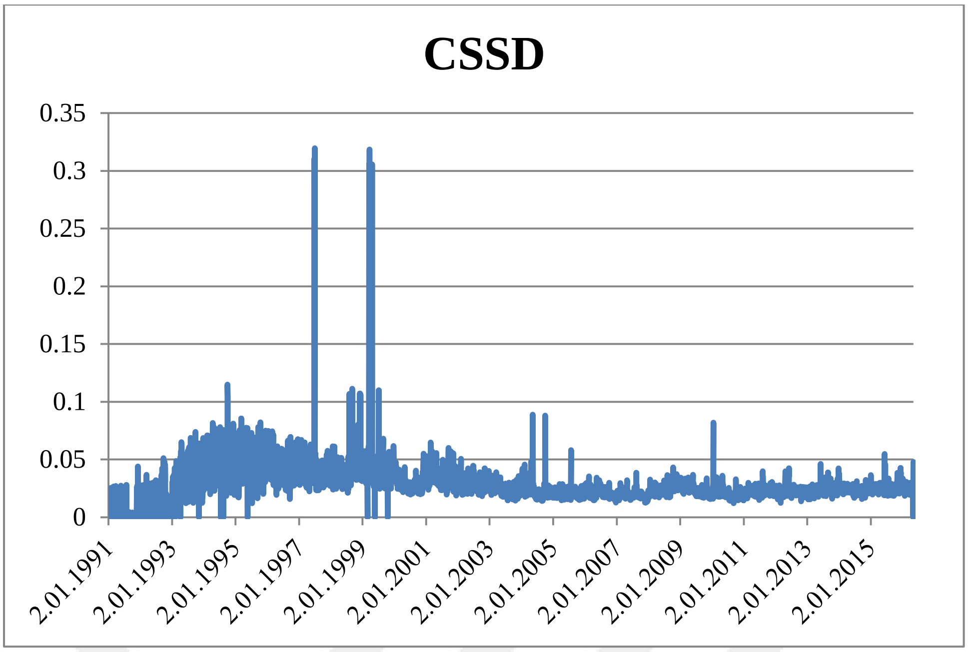

Figure 5.Time series plot of cross-sectional standard deviations of returns

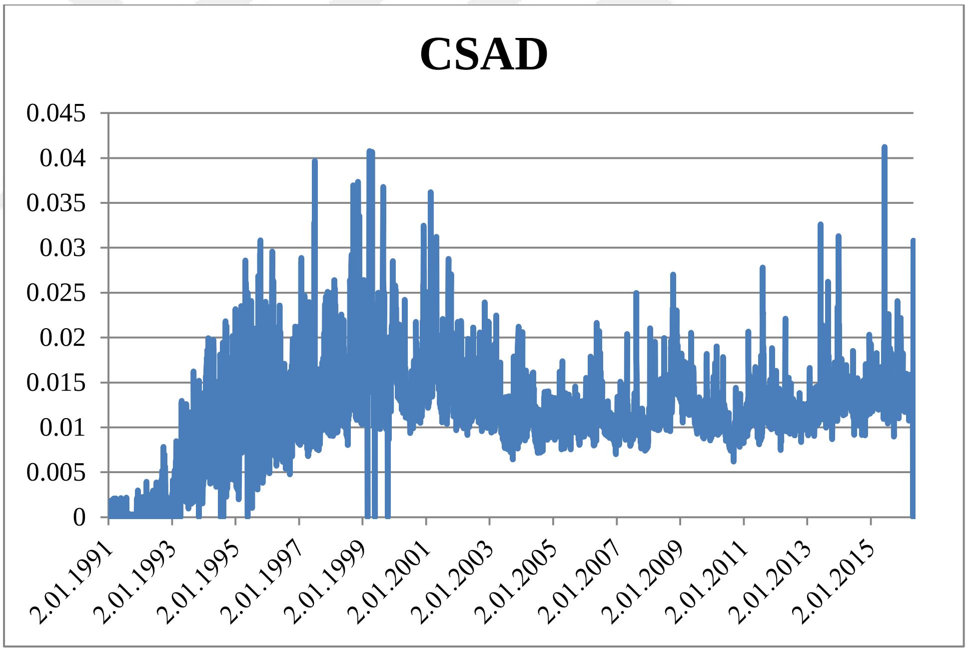

Figure 6.Time series plot of cross-sectional absolute deviations of returns

Fig.5 and Fig. 6 display cross-sectional standard deviations and cross-sectional absolute deviations. CSSD exhibits more stable volatility than CSAD, especially after 1999. CSAD indicates sharp declines and increases. Both of them clearly show some spikes in 1999. These may be caused by financial crisis and earthquake which happened in August 17, 1999.

6.2. Regression Analysis Approaches

In this section, we mention some methods for investigating herd behavior. We begin with two common methods which are proposed by Christie and Huang (1995) (hereafter CH) and Chang et al. (2000) (hereafter CCK). Then, we employ quantile regression on CCK method like Tan et al. (2010).

6.2.1. Evidence of herding

We start our study of existence of herd behavior by employing dummy variables regression tests with CH (1995) approach. Christie and Huang (1995) use the 1% and 5% criterion to determine the upper and lower tail of the market return distribution to define extreme price movement days. If the coefficients β_1 and β_2 are negative and statistically significant, it indicates herd behavior.

Table 2. Regression results of the daily cross sectional standard deviation during periods of market stress with dummy variables

Variable	1% Criterion			
	α	β_1	β_2	$\bar{R}^2$
$CSSD_t$	0.028	-0.025	-0.005	0.023
	(137.97)***	(-26.07)***	(-6.31)***	
	5% Criterion			
	0.030	-0.025	-0.004	0.011
	(139.71)***	(-48.40)***	(-12.75)***	

Heteroscedasticity consistent t-statistics are reported in parentheses.

*** The coefficient is significant at the 1% level.

Table 2 and 3 report the estimation results of following regression model:

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t \quad (4.2)$$

where D_t^L (D_t^U) equals 1 if the market return on day *t* lies in the extreme lower (upper) tail of return distribution, otherwise D_t^L (D_t^U) equals zero.

The results in Table 2 show us for $CSSD_t$, the coefficients β_1 and β_2 are negative and statistically significant for extreme price movement days with both criteria and this is an evidence of herd behavior. It means that there is a decrease in $CSSD_t$ during days corresponding to extreme upward and downward price movements.

Table 3. Regression results of the daily cross sectional standard deviation during periods of market stress with dummy variables after 2000

Variable	1% Criterion			
	α	β_1	β_2	$\bar{R}^2$
$CSSD_t$	0.024	0.016	0.015	0.116
	(260.96)***	(12.15)***	(12.04)***	
	5% Criterion			
	0.233	0.009	0.008	0.174
	(264.10)***	(15.61)***	(15.71)***	

Heteroscedasticity consistent t-statistics are reported in parentheses.

*** The coefficient is significant at the 1% level.

The results in Table 3 show us, when we use the data after 2000, the coefficients β_1 and β_2 are statistically significant but not negative and this is evidence that there is no herd behavior for extreme price movement days with both criteria after 2000.

Table 4. Regression results of the daily cross sectional absolute deviation during periods of market stress with dummy variables

Variable	1% Criterion			
	α	β_1	β_2	$\bar{R}^2$
$CSAD_t$	0.012	-0.011	0.001	0.048
	(180.17)***	(-120.88)***	(1.92)*	
	5% Criterion			
	0.012	-0.012	0.002	0.253
	(195.49)***	(-161.89)***	(9.89)***	

Heteroscedasticity consistent t-statistics are reported in parentheses.

* The coefficient is significant at the 10% level.

*** The coefficient is significant at the 1% level.

Table 4 and 5 report the estimation results of following regression models:

$$CSAD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t \tag{4.3}$$

where D_t^L (D_t^U) equals 1 if the market return on day t lies in the extreme lower (upper) tail of return distribution, otherwise D_t^L (D_t^U) equals zero.

When we compare the results in Table 4 with those of Table 2, we see that $CSAD_t$ measure presents different results for up market. The coefficients β_1, which are associated with down market, are negative and statistically significant for both criteria and this result is consistent with $CSSD_t$. Thus, we can say investors exhibit herd behavior in down market for extreme price movements. However, the coefficients β_2, which are associated with up market, are positive and statistically significant. This means there is no herd behavior for up market and dispersion of returns display increases rather than decreases during extreme price movements.

Table 5. Regression results of the daily cross sectional absolute deviation during periods of market stress with dummy variables after 2000

Variable	1% Criterion			
	α	β_1	β_2	$\bar{R}^2$
$CSAD_t$	0.013	0.011	0.008	0.180
	(277.69)***	(16.72)***	(13.72)*	
	5% Criterion			
	0.012	0.006	0.005	0.297
	(304.41)***	(18.77)***	(19.26)***	

Heteroscedasticity consistent t-statistics are reported in parentheses.

* The coefficient is significant at the 10% level.

*** The coefficient is significant at the 1% level.

Table 5 indicates us, when we reexamine herd behavior by using the data after 2000, the coefficients β_1 and β_2 are statistically significant but not negative. Then we conclude that investors do not herd in the market after 2000.

Besides, $\bar{R}^2$ are too small for both all models. For the following analyses, the results always exhibit small $\bar{R}^2$. We can explain hypothesize that herd behavior is not the only reason for changes in dispersion of returns during price movement periods. There may be lots of different fundamental factors that affect the market in this way. However, we do not include other factors in the models because the aim of this thesis is to investigate herd behavior.

In this section we reexamine herd behavior in BIST with the approach developed by Chang et al. (2000) developed approach. They extended the CH approach by including nonlinear relation between return dispersion and the overall market return. If investors tend to follow market behavior despite their own priors during periods of large price swings, the relation between dispersion and average market return will no longer be linear. Because of this, a nonlinear market return is included in the equation and thereby, the relation will not be linearly increasing or decreasing. In other words, returns dispersion will decrease (or increase at a decreasing rate) with an increase in the market return if there is herd behavior. They used cross-sectional absolute deviation of returns (CSAD) as a measure of returns dispersion. Likewise, absolute values are used to facilitate a comparison of the coefficients of the linear term to capture asymmetric effects arising from market rising of falling markets.[10]

This nonlinear relation is built with following regression models and the estimation results are reported in Table 6 and 7:

$$CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{4.5}$$

$$Model\ A: CSAD_t^{Up} = \gamma_0 + \gamma_1^{Up} |R_{m,t}^{Up}| + \gamma_2^{Up} \left(R_{m,t}^{Up}\right)^2 + \varepsilon_t \tag{4.6}$$

$$Model\ B: CSAD_t^{Down} = \gamma_0 + \gamma_1^{Down} |R_{m,t}^{Down}| + \gamma_2^{Down} \left(R_{m,t}^{Down}\right)^2 + \varepsilon_t \tag{4.7}$$

where $|R_{m,t}^{Up}| [|R_{m,t}^{Down}|]$ is the absolute value of an equally weighted return of all available securities on day *t* when the market is up [down] and $\left(R_{m,t}^{Up}\right)^2 \left[\left(R_{m,t}^{Down}\right)^2\right]$ is the squared value of this term. $\bar{R}^2$ is the adjusted R^2.

[10] The analysis needs to write an alternative equation and Tan et al. (2010) applied this alternative equation. The next section analysis includes this.

Table 6 demonstrates the estimation results of herding based on CKK approach for the market as well as the up and down markets separately. The presence of negative and statistically significant non linearity coefficient is an indicator of herd behavior in the model. Starting with the market regression; we can see that non linearity coefficient γ_2 is negative and statistically significant which means herd behavior exists in the Turkey stock market BIST. This means return dispersion decreases if the average price movement increases. When we investigate herding under the up and down markets, the estimated coefficients γ_2^{Up} and γ_2^{Down} are both negative and statistically significant. The results are an indicator that investors display herding behavior in up and down markets.

Table 6. Regression results of cross-sectional absolute deviation of the market and up and down markets

Variable	γ_0	γ_1	γ_2	$\bar{R}^2$
$CSAD_t$	0.009	0.227	-1.244	0.208
	(105.52)***	(31.05)***	(-21.09)***	
		Model A		
$CSAD_t$	γ_0	γ_1^{Up}	γ_2^{Up}	$\bar{R}^2$
	0.010	0.199	-1.109	0.172
	(85.65)***	(19.76)***	(-17.18)***	
		Model B		
$CSAD_t$	γ_0	γ_1^{Down}	γ_2^{Down}	$\bar{R}^2$
	0.009	0.229	-1.246	0.220
	(71.48)***	(20.99)***	(-11.55)***	

Heteroscedasticity consistent *t*-statistics are reported in parentheses.

*** The coefficient is significant at the 1% level.

Table 7 shows the estimation results of herding based on CKK approach for the market as well as the up and down markets separately after 2000. The negative and statistically significant non linearity coefficients are an indicator of herd behavior in the market and up and down markets. So, our new results are consistent with the previous results for CCK approach.

Table 7. Regression results of cross-sectional absolute deviation of the market and up and down markets after 2000

Variable	γ_0	γ_1	γ_2	$\bar{R}^2$
CSAD_t	0.011	0.177	-0.432	0.418
	(181.35)***	(26.03)***	(-4.85)***	
		Model A		
CSAD_t	γ_0	γ_1^{Up}	γ_2^{Up}	$\bar{R}^2$
	0.011	0.176	-0.476	0.365
	(131.83)***	(18.78)***	(-3.97)***	
		Model B		
CSAD_t	γ_0	γ_1^{Down}	γ_2^{Down}	$\bar{R}^2$
	0.011	0.175	-4.407	0.455
	(127.42)***	(19.08)***	(-3.63)***	

Heteroscedasticity consistent *t*-statistics are reported in parentheses.
*** The coefficient is significant at the 1% level.

Table 8 and 9 report the estimation results of following alternative regression models, respectively:

$$CSAD_t = \gamma_0 + \gamma_1(1-D)R_{m,t} + \gamma_2 DR_{m,t} + \gamma_3 R_{m,t}^2 + \varepsilon_t \quad (4.8)$$

$$CSAD_t = \gamma_0 + \gamma_1(1-D)R_{m,t} + \gamma_2 DR_{m,t} + \gamma_3(1-D)R_{m,t}^2 + \gamma_4 DR_{m,t}^2 + \varepsilon_t \quad (4.9)$$

where D is a dummy variable which equals 1 when $R_{m,t} < 0$ and D=0 otherwise, $R_{m,t}$ is the equally weighted market portfolio return at time *t*. CSAD_t is the equally weighted cross-sectional absolute deviation of returns. $\bar{R}^2$ is the adjusted R^2.

As we mentioned above, table 8 contains the alternative equation results to examine herding and also demonstrate the asymmetric characteristics of returns (see, e.g. Tan et al. 2010, Zhou and Anderson 2011). We see whether herd behavior shows an asymmetric effect or not on days when market is up or down. Like in the previous models, if non linearity coefficients are negative and statistically significant, herd behavior occurs in the market. The statistics reported in Panel A represent the whole market and non-linearity coefficient γ_3 is negative and statistically significant which indicates herd behavior in the Turkey stock market BIST. The statistics reported in Panel B represent the up and down markets. Here, the coefficients γ_1 and γ_3 are for the up market and the coefficients γ_2 and γ_4 are for the down market. The non-linearity coefficients are negative and statistically significant. Thus, we can conclude that investors herd in the up and down markets.

We are also able to find chance to test the equality of the herding coefficient between the up and down markets.[11] The null hypothesis $\gamma_3 = \gamma_4$ cannot be rejected. That means we can assume investors who live in Turkey, respond to good and bad economic news symmetrically for both up and down markets.

When we look at the analyses with the data after 2000 with alternative equation, as it can be seen from table 9, the results do not change. So, we can conclude that like the prior model, herd behavior exist in the market. Besides, the result for the equality of herding coefficient is consistent with the prior which means investors react to economic news similarly in the up and down markets.

[11] There are lots of studies that return dispersion and correlations display different behavior in rising and declining markets (see McQueen at al. (1996); Bekaert and Wu (2000); Duffee (2000)).

Table 8. Regression results of cross-sectional absolute deviation of the market and up and down markets with the alternative equation

Variable	γ_0	γ_1	γ_2	γ_3	$\bar{R}^2$
Panel A: Statistics for the entire market					
$CSAD_t$	0.009	0.222	-0.231	-1.238	0.208
	(104.52)***	(24.89)***	(-28.51)***	(-20.31)***	

Panel B: Statistics for the up and down markets

	Up Market			Down Market			Wald coefficient test
	γ_0	γ_1	γ_3	γ_2	γ_4	$\bar{R}^2$	$H_0: \gamma_3 = \gamma_4$ $H_1: \gamma_3 \neq \gamma_4$
	0.009	0.220	-1.215	-0.234	-1.275	0.208	0.608
	(104.43)***	(24.73)***	(-18.43)***	(-25.05)***	(-12.34)***		

Heteroscedasticity consistent *t*-statistics are reported in parentheses.

Also *p*-values of Wald hypotheses test are reported for $\gamma_3 = \gamma_4$.

*** The coefficient is significant at the 1% level.

Table 9. Regression results of cross-sectional absolute deviation of the market and up and down markets with the alternative equation after 2000

Variable	γ_0	γ_1	γ_2	γ_3	$\bar{R}^2$
Panel A: Statistics for the entire market					
$\mathrm{CSA}D_t$	0.011 (184.47)***	0.168 (23.20)***	-0.185 (-26.09)***	-0.453 (-5.67)***	0.420

Panel B: Statistics for the up and down markets

	Up Market			Down Market			Wald coefficient test
	γ_0	γ_1	γ_3	γ_2	γ_4	$\bar{R}^2$	$H_0: \gamma_3 = \gamma_4$ $H_1: \gamma_3 \neq \gamma_4$
	0.011 (180.63)***	0.164 (19.15)***	-0.372 (-2.80)***	-0.188 (-24.47)***	-0.508 (-5.09)***	0.420	0.337

Heteroscedasticity consistent *t*-statistics are reported in parentheses.

Also *p*-values of Wald hypotheses test are reported for $\gamma_3 = \gamma_4$.

*** The coefficient is significant at the 1% level.

6.2.2. Quantile regression approach

While some researchers employ ordinary least square regression to detect herding, some use quantile regression (QR) (Koenker and Bassett 1978). This approach provides to seek herding in different quantiles of stock return dispersion, not just extreme tails. Besides, it solves some statistical problems such as non-normal distributions, errors in variables, omitted variables bias, sensitivity to outliers (Koenker 2005; Barnes and Hughes 2002). Therefore, we reexamine our returns dispersion with quantile regression. Like the earlier analyses, the negative and statistically significant non-linear coefficient is an indicator of herd behavior.

Table 10 and 11 reports the estimation results of following quantile regression model by different $CSAD_t$ quantile groups:

$$Q_r(\tau|X_t) = \gamma_{0,\tau} + \gamma_{1,\tau}|R_{m,t}| + \gamma_{2,\tau}R_{m,t}^2 + \varepsilon_{\tau,t} \qquad (4.14)$$

Where $CSAD_t$ is the cross-sectional absolute deviation of returns which is dependent variable and $R_{m,t}$ is the equally weighted market portfolio return at time *t*. X_t represents a vector of right-hand-side variables on the above equation and D is a dummy variable which equals 1 when $R_{m,t}$< 0 and D=0 otherwise. $\gamma_{k,\tau}$ refers to the *k*th coefficient conditional on *τ*th quantile distribution in the estimated equation.

Table 10 presents the estimation results of herding for all market by using quantile regression method. The coefficient γ_2 is negative and statistically significant for all different quantiles. So based on the QR results, again, we find evidence of herd behavior in Turkey stock market BIST in all quantiles. In general, its effect decreases when the quantile rises and also we can say herd behavior exist in the normal market conditions like in median quantile (τ=50%).

To see herding better, we plot the quantile plot of herding coefficients in Fig. 7. As it can be seen clearly on Fig 7., return dispersion increases at a decreasing rate, in other words herding pattern continues from low quantiles to high quantiles. After these results, we can state that investors tend to herd during non-extreme market conditions. This result is consistent with findings of Hwang and Salmon (2004).

Table 10. Quantile regression results of cross-sectional absolute deviation on all market

Variable	γ_0	γ_1	γ_2	Pseudo R^2
Quantile (τ=10%)	0.002	0.218	-1.569	0.024
	(2.5)***	(5.82)***	(-6.60)***	
Quantile (τ=25%)	0.008	0.177	-1.26	0.051
	(80.81)***	(16.78)***	(-16.38)***	
Quantile (τ=50%)	0.010	0.220	-1.184	0.121
	(142.24)***	(35.09)***	(-38.81)***	
Quantile (τ=75%)	0.011	0.252	-1.107	0.223
	(163.86)***	(38.81)***	(-14.00)***	
Quantile (τ=90%)	0.013	0.270	-0.941	0.321
	(86.85)***	(10.44)***	(-1.77)*	

Heteroscedasticity consistent *t*-statistics are reported in parentheses.

* The coefficient is significant at the 10% level.

*** The coefficient is significant at the 1% level.

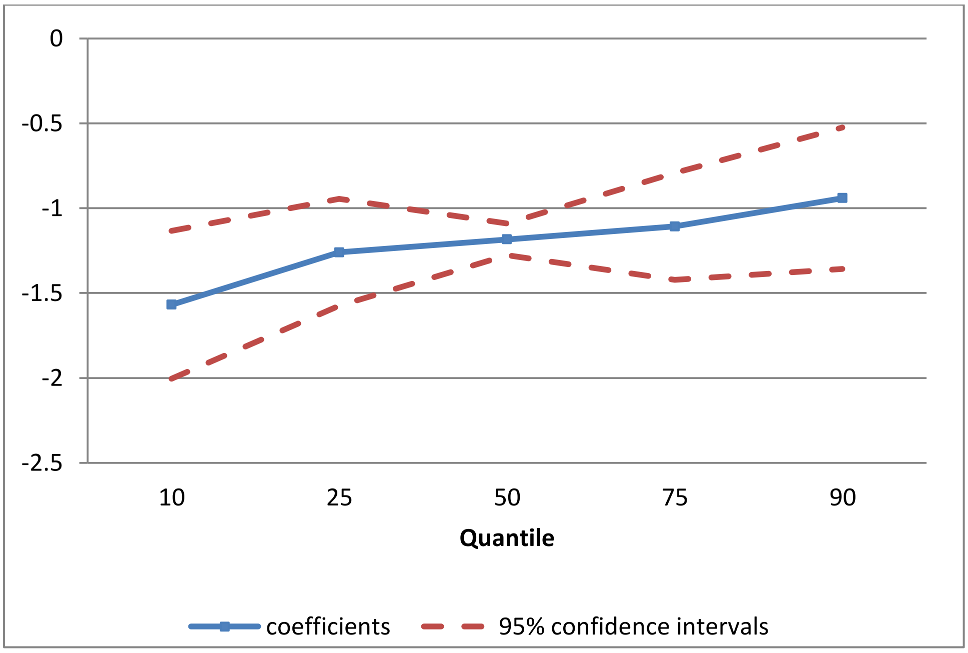

Figure 7.Quantile plots of the herding coefficients for the market

Table 11 represents the results for all market after 2000 by using quantile regression method. The coefficients γ_2, which are an indicator of herd behavior, are negative and statistically significant in the quantiles from 10% to 75% but not significant in the quantile 90%. So based on these results, we find partial evidence in the median quantile and no evidence in the highest quantile although we find evidence in the median quantile and partial evidence in the highest quantile in our previous results for the whole sample.

Table 11. Quantile regression results of cross-sectional absolute deviation on all market after 2000

Variable	γ_0	γ_1	γ_2	Pseudo R^2
Quantile (τ=10%)	0.008	0.146	-0.380	0.140
	(118.08)***	(21.45)***	(-7.47)***	
Quantile (τ=25%)	0.009	0.149	-0.300	0.155
	(157.24)***	(23.02)***	(-4.06)***	
Quantile (τ=50%)	0.010	0.155	-0.276	0.188
	(144.14)***	(16.05)***	(-1.65)*	
Quantile (τ=75%)	0.012	0.187	-0.371	0.251
	(143.83)***	(17.10)***	(-2.31)**	
Quantile (τ=90%)	0.013	0.207	-0.316	0.332
	(127.34)***	(12.72)***	(-1.17)	

Heteroscedasticity consistent *t*-statistics are reported in parentheses.

* The coefficient is significant at the 10% level.

** The coefficient is significant at the 5% level

*** The coefficient is significant at the 1% level.

Table 12. Quantile regression results of cross-sectional absolute deviation on up and down markets

Variable		Up Market		Down Market		Pseudo R^2	Wald coefficient test
	γ_0	γ_1	γ_3	γ_2	γ_4		$H_0: \gamma_3 = \gamma_4$ $H_1: \gamma_3 \neq \gamma_4$
Quantile($\tau = 10\%$)	0.002	0.218	-1.572	-0.182	-1.332	0.024	0.505
	(2.68)***	(5.89)***	(-6.27)***	(-2.86)***	(-3.10)***		
Quantile($\tau = 25\%$)	0.008	0.175	-1.267	-0.178	-1.187	0.051	0.483
	(76.13)***	(13.36)***	(-11.98)***	(-14.33)***	(-14.65)***		
Quantile($\tau = 50\%$)	0.010	0.211	-1.143	-0.225	-1.205	0.121	0.840
	(103.40)***	(21.01)***	(-25.89)***	(-11.89)***	(-3.72)***		
Quantile($\tau = 75\%$)	0.011	0.251	-1.264	-0.250	-0.940	0.224	0.114
	(149.64)***	(34.00)***	(-41.03)***	(-19.52)***	(-4.42)***		
Quantile($\tau = 90\%$)	0.013	0.272	-1.115	-0.281	-0.997	0.321	0.953
	(60.40)***	(3.78)***	(-0.53)	(-15.19)***	(-4.87)***		

Heteroscedasticity consistent *t*-statistics are reported in parentheses.
Also reported are *p*-values of Wald hypotheses test for $\gamma_3 = \gamma_4$.
*** The coefficient is significant at the 1% level.

Table 13. Quantile regression results of cross-sectional absolute deviation on up and down markets after 2000

Variable	Up Market γ_0	γ_1	γ_3	Down Market γ_2	γ_4	Pseudo R^2	Wald coefficient test $H_0: \gamma_3 = \gamma_4$ $H_1: \gamma_3 \neq \gamma_4$
Quantile($\tau = 10\%$)	0.008	0.141	-0.353	-0.150	-0.472	0.140	0.302
	(117.88)***	(17.48)***	(-6.45)***	(-18.17)***	(-6.49)***		
Quantile($\tau = 25\%$)	0.009	0.137	-0.231	-0.158	-0.320	0.157	0.196
	(163.57)***	(19.31)***	(-3.49)***	(-25.80)***	(-8.25)***		
Quantile($\tau = 50\%$)	0.011	0.135	0.108	-0.171	-0.427	0.190	0.051*
	(140.72)***	(9.59)***	(0.38)	(-19.06)***	(-7.78)***		
Quantile($\tau = 75\%$)	0.012	0.149	0.193	-0.209	-0.600	0.256	0.407
	(104.23)***	(4.56)***	(0.19)	(-20.00)***	(-4.82)***		
Quantile($\tau = 90\%$)	0.013	0.163	0.445	-0.229	-0.614	0.336	0.015**
	(125.37)***	(7.01)***	(0.98)	(-19.00)***	(-5.75)***		

Heteroscedasticity consistent *t*-statistics are reported in parentheses.
Also reported are *p*-values of Wald hypotheses test for $\gamma_3 = \gamma_4$.
* The coefficient is significant at the 10% level.
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level.

Table 12 and 13 report the estimation results of following quantile regression model by different $CSAD_t$ quantile groups:

$$Q_r(\tau|X_t) = \gamma_{0,\tau} + \gamma_{1,\tau}(1-D)R_{m,t} + \gamma_{2,\tau}DR_{m,t} + \gamma_{3,\tau}(1-D)R_{m,t}^2 + \gamma_{4,\tau}DR_{m,t}^2 + \varepsilon_{\tau,t} \quad (4.15)$$

where $CSAD_t$ is the equally weighted cross-sectional absolute deviation of returns which is dependent variable and $R_{m,t}$ is the equally weighted market portfolio return at time *t*. X_t represents a vector of right-hand-side variables on the above equation and D is a dummy variable which equals 1 when $R_{m,t}$< 0 and D=0 otherwise. $\gamma_{k,\tau}$ refers to the *k*th coefficient conditional on *τ*th quantile distribution in the estimated equation.

Table 12 reports the estimation results of herding in up and down markets using quantile regression method. The estimated statistics show us that both γ_3 and γ_4 are negative and statistically significant in the quantiles$\tau = 10\%, \tau = 25\%, \tau = 50\%$ and $\tau = 75\%$ for up and down markets which means that herd behavior occurs in these quantiles and markets. However, when we consider the quantile $\tau = 90\%$, the results are slightly different from the earlier analyses. In the highest quantile ($\tau = 90\%$), the coefficient γ_4, which is an indicator for down market, is negative and statistically significant. Though, the coefficient γ_3, which is an indicator for up market, is negative but not statistically significant. So, although investors herd in down market at all quantile levels, there is no herd behavior in up market when the market is at extreme quantile of distribution. Moreover, the pattern of herding can be seen from quantile plot of herding coefficients in Fig. 8 and Fig. 9 for up and down markets. Thus, when we check to robustness of herding with the data after 2000, the results have some differences from previous ones and these differences are shown in table 13. The estimation results are same for the down market in the all quantiles. However, when we consider the up market, there is no longer herd behavior in the quantiles from 50% to 90%. Also, the results of testing the equality of herding coefficient demonstrate that investors react differently to economic news in up and down markets in the quantiles 50% and 90%.

We also test the equality of herding coefficient between the up and down markets. The null hypothesis $\gamma_3 = \gamma_4$ cannot be rejected in all quantile levels for both up and down markets. That means we can assume investors in Turkey react similarly to up and down markets.

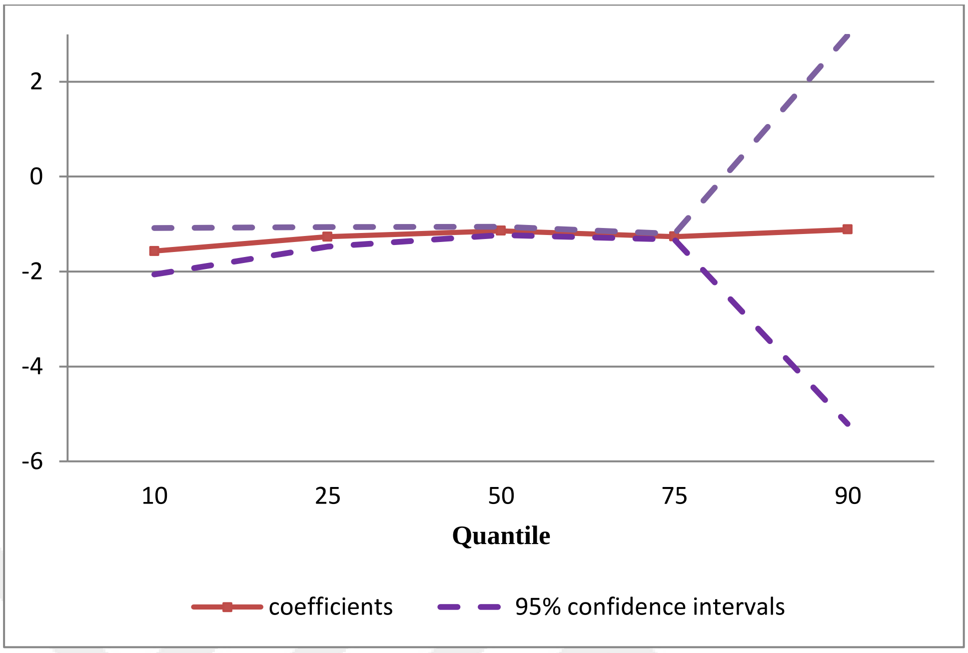

Figure 8.Quantile plot of the herding coefficients for the up market

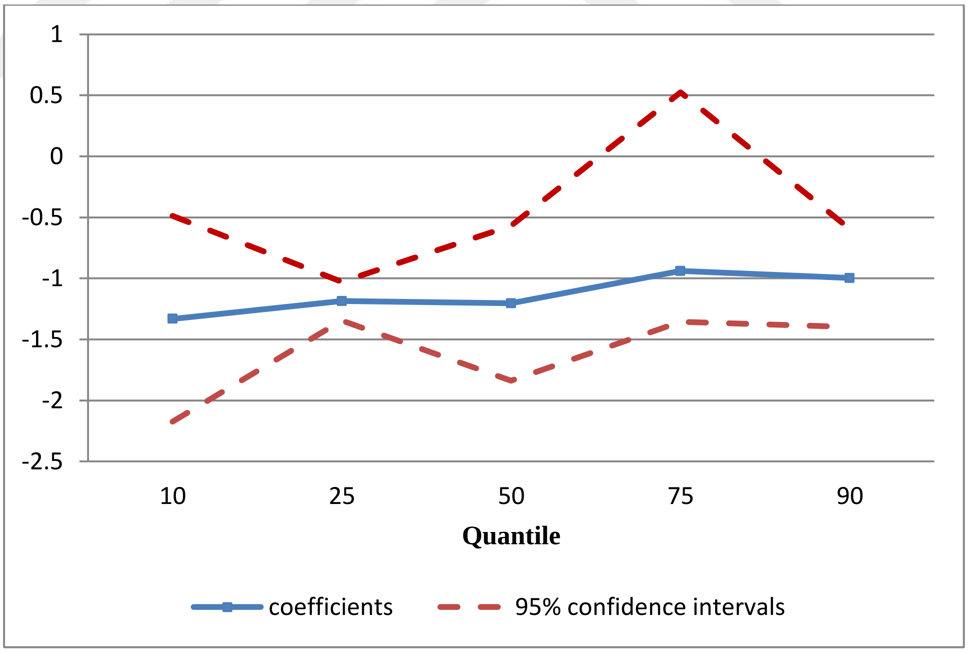

Figure 9.Quantile plot of the herding coefficients for the down market

6.3. State-Space Approach

In this section, we employ Hwang and Salmon (2004) method to investigate herding and it is based on state-space models. This approach centers on cross-sectional variability of factor sensitivity rather than returns and hence, the measure is not influenced by idiosyncratic components such as movements in fundamentals, investors characteristics, problem of time series volatility. According to their model, the capital asset pricing model (CAPM) betas of individual assets will be biased away from their equilibrium when investors herd toward the market portfolio. We need to estimate the betas and calculate cross-sectional standard deviation of the betas to be used in state space models. For estimation of betas, we use monthly observations as in Hwang and Salmon (2004). To reduce estimation error in the beta estimates, like Hwang and Salmon (2004) we use 1-month's data at a time to estimate the betas. Therefore, the betas are calculated with daily data over monthly intervals by using standard ordinary least squares (OLS) as in the following equation;

$$r_{it_d} = \alpha_{it}^{b} + \beta_{imt}^{b} r_{im_d} + \varepsilon_{it_d} \tag{4.25}$$

where r_{it_d} represents to daily excess return of stock i, r_{im_d} refers the daily excess returns of the market for the month *t*. In other words, the subscript t_d denotes daily data *d* for the given month *t*. Excess returns are calculated with 3 month Treasury bill for Turkey. Then, with these estimated betas we create a monthly time series by calculating the cross-sectional standard deviations of the betas. Also, after estimation of betas, we get the cross-sectional standard deviation of the monthly betas as following;

$$Std_c\left(\beta_{imt}^{b}\right) = \sqrt{\frac{\sum_{i=1}^{N_t}\left(\beta_{imt}^{b} - \overline{\beta_{imt}^{b}}\right)^2}{N_t}} \tag{4.26}$$

where $\overline{\beta_{imt}^{b}} = \frac{1}{N_t}\sum_{i=1}^{N_t} \beta_{imt}^{b}$ and N_t is the number of equities in month *t*.

A total number of 1,326,848 daily observations from 2 January 2001 to 29 April 2016 are used. For each month, daily returns of the month are used to estimate betas of each stock and they are used to calculate cross-sectional standard deviation of betas of the month. After OLS, we get 68,461 betas. We take betas that are computed with 17 and more observations for each month to calculate the cross-sectional standard deviations. The only exceptions are February, 2003 and November, 2003, for which we allow 15 and 13 observations respectively, in order to obtain a complete time series for the period January 2001 and April 2016. OLS regressions with sufficient number of observations generate 63,106 betas from which we obtain a total number of 184 monthly cross-sectional standard deviation of betas.

Table 14. Descriptive statistics of cross-sectional standard deviation of betas and log cross-sectional standard deviation of betas

	Cross-sectional standard deviation of betas	Logarithmic cross-sectional standard deviation of betas
Mean	0.356	-1.097
Std. Dev.	0.123	0.372
Min	0.069	-2.677
Max	0.770	-0.262
Skewness	0.635	-0.762
Kurtosis	3.735	4.776
Jarque-Bera	16.505	42.014

Table 14 reports some statistical properties about some the estimated cross-sectional standard deviations and the logarithmic cross-sectional standard deviations of the betas on market portfolio. To test normality of distributions, we use Jarque-Bera statistics as follows;

$$JB = n\left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right] \tag{4.27}$$

$$\alpha = 0.05\ \chi^2(2) = 5.991$$

where n represents number of months, S is skewness and K is kurtosis. If JB is greater than the value of $\chi^2_{\alpha,df}$, null hypothesis which is an indicator of normal distribution is rejected.

So, we cannot say those cross-sectional standard deviations of betas and the logarithmic cross-sectional standard deviations of the betas are normally distributed.

When we examine the distribution of logarithmic cross-sectional deviations of betas, as it can be seen from Fig.10, there are three extreme values. Those extreme values are February 2001, March 2001 and June 2013. If these three extreme values are excluded from the distribution, Jarque-Bera statistics of cross-sectional standard deviations of betas and the logarithmic cross-sectional standard deviations of the betas become respectively 22.465 and 1.534. Thus, logarithmic cross-sectional deviation of betas does not deviate from the Gaussian distribution. However, we continue our analysis with the whole sample since we need a complete time series. Besides, if non-normal errors are suspected, Huber-White robust standard errors can be used as discussed in Drukker and Gates (2011).[12] So, we use robust standard errors method in our state-space model and the results are reported in Table 15.

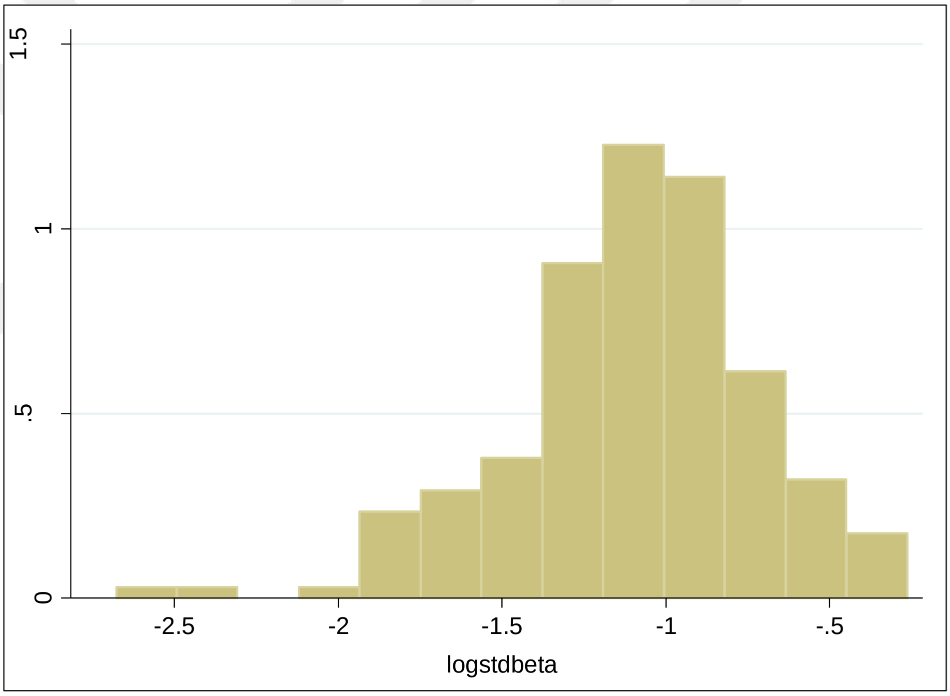

Figure 10.Histogram of logarithmic cross-sectional standard deviation of betas

The state-space models are estimated by following equations;

Model 1;

$$log\left[Std_c\left(\beta_{imt}^{b}\right)\right] = \mu_m + H_{mt} + \upsilon_{mt} \tag{4.22}$$

$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt} \tag{4.23}$$

[12]With vce (robust) command, Huber-White robust standard errors can be obtained in Stata12. Also more information about vce (robust) can be found StataCorp 2012a &StataCorp 2012b

Model 2;

$$\log\left[Std_c\left(\beta_{imt}^b\right)\right] = \mu_m + H_{mt} + c_{m1} log\sigma_{mt} + c_{m2} r_{mt} + v_{mt} \qquad (4.24)$$

$$H_{mt} = \varphi_m H_{mt-1} + \eta_{mt} \qquad (4.23)$$

where $log\sigma_{mt}$ is log volatility and r_{mt} is return at time t.[13] Proportion of signal is $\sigma_{m\eta}$(the standard deviation of the state equation error η_{mt}) to standard deviation of $\log\left[Std_c\left(\beta_{imt}^b\right)\right]$. Proportion of signal is an indicator that total variability in $Std_c\left(\beta_{imt}^b\right)$ which is due to herding. Moreover, if herding parameters φ_m and $\sigma_{m\eta}$are significant, we can conclude that there is herding in the market.

We first investigate herding with Model 1. Both herding parameters are significant and H_{mt} is highly persistent with φ_m large. So, we can say herding occurs towards the market portfolio and herding explains 50% of total variability in $Std_c\left(\beta_{imt}^b\right)$.

Table 15 also reports results for Model 2 when we include market volatility and market return. Two herding parameters are still significant and H_{mt} is highly persistent with $\varphi_m$large. Here, herding is able to explain 31% of total variability in $Std_c\left(\beta_{imt}^b\right)$. The volatility parameter is negative and significant. Thus, $Std_c\left(\beta_{imt}^b\right)$ decreases when market volatility rises due to increase in the herding. In other words, $Std_c\left(\beta_{imt}^b\right)$ decreases, when market is falling and becomes riskier while it increases when the market rises and becomes less risky. However, market return coefficient is not found significant. So, we can conclude that there is no relationship between market returns and $Std_c\left(\beta_{imt}^b\right)$.

---

[13] As we mentioned in the chapter 4, the monthly market volatility is calculated by using square daily returns as in Schwert (1989).

Table 15. Estimates of State-Space Models for Herding

Variable	No exogenous variables (Model 1)	Excess market return and volatility (Model 2)
μ	-1.104	-1.419
	(-15.53)***	(-37.25)***
φ_m	0.791	0.683
	(6.65)***	(7.30)***
σ_{mv}	0.230	0.312
	(3.45)***	(4.95)***
$\sigma_{m\eta}$	0.184	0.116
	(2.04)**	(2.83)***
$log\sigma_m$	-	-0.433
		(-13.52)***
r_m	-	1.419
		1.07
Proportion of signal	0.495	0.313
Log likelihood values	-51.470	14.097
AIC	110.941	-16.193
SIC	123.803	3.097

AIC, Akaike information criterion

SIC, Schwarz information criterion

** The coefficient is significant at the 5% level.

*** The coefficient is significant at the 1% level.

Figure 11 display the evolution of our herding measure h_{mt} $(= 1 - \exp(H_{mt}))$ in the Turkish market calculated with the cross-sectional standard deviation of betas using Model 1. CSSD betas are the cross-sectional standard deviation of betas and herding represents the values of herding measure. We can see that the value of h_{mt} is bounded between -0.20 and 0.29. The figure shows several cycles of herding around its long-term average of zero over the last 13 years since 2003.

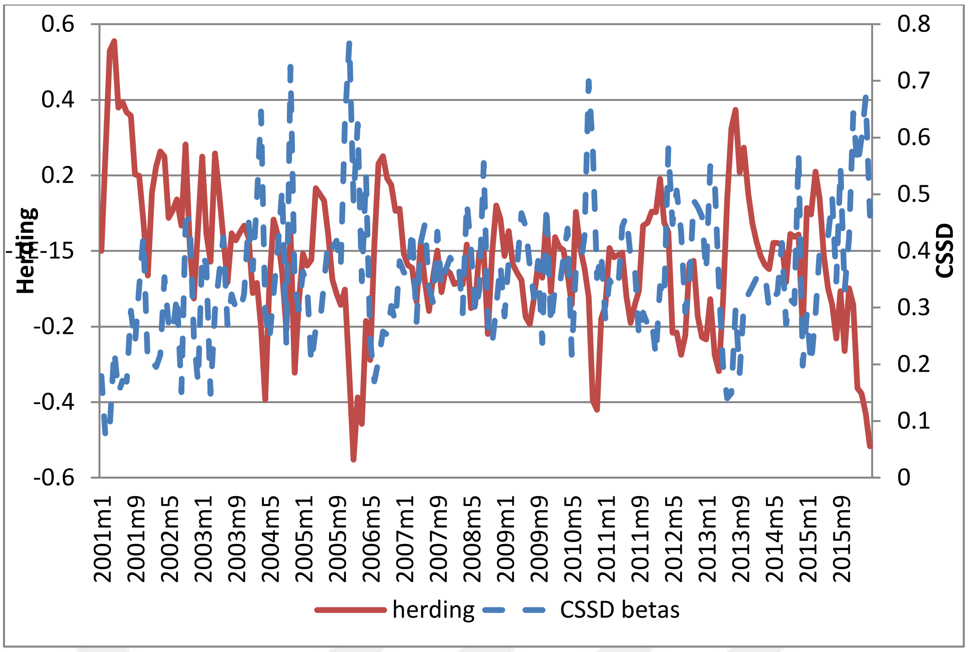

Figure 11.Time path of herding towards market and cross-sectional standard deviation of betas

As can be seen from Fig. 11, herding is significantly different from zero for some periods. These are from February to September 2001, March and September 2002, January and April 2003, April and September 2004, January, March and August 2006, October and November 2010, July, August and September 2013 and the last one is April 2016. The highest level of herding is around April 2001. Moreover, it is clearly seen that there is adverse relation between h_{mt} and the cross-sectional standard deviations of betas. When there is a decrease in the CSSD betas, h_{mt} increases or vice versa.

Figure 12 also shows the time path of our herding measure when we include market volatility and market return in state-space model. Vol represent market volatility, rm is the market return and herding is the variable h_{mt} and CSSD betas are the cross-sectional standard deviation of betas. Without any doubt that, herd behavior increases with increase in market volatility and when volatility increases (decreases), CSSD betas decreases (increases) and also, market returns have no effect on herding.

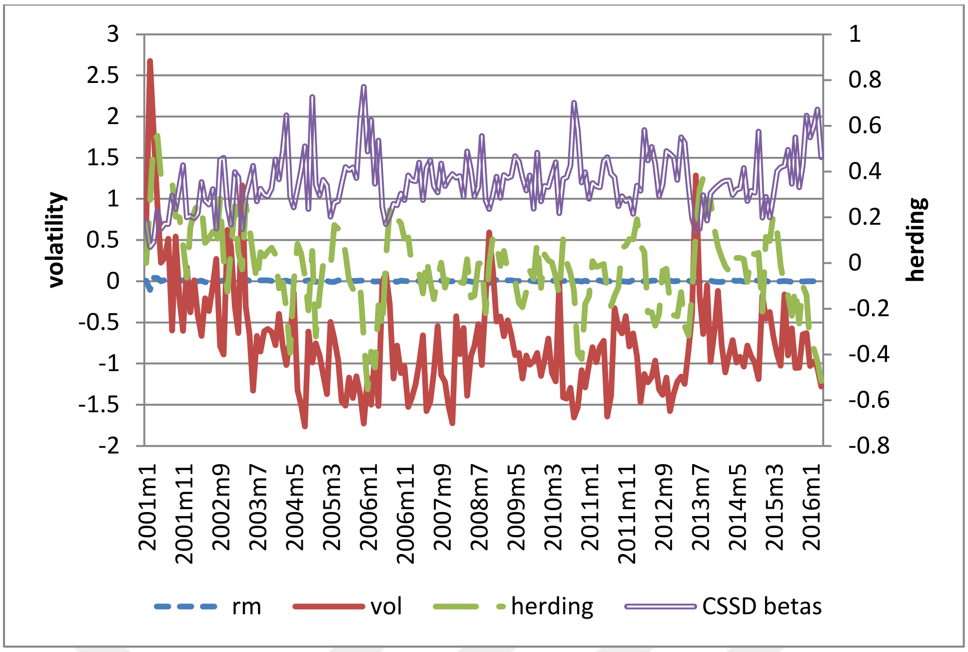

Figure 12.Herding when market return and volatility are included in the state-space model

6.4. Granger Causality Test

In order to highlight the robustness, we examine what causes herd behavior in the market with Granger Causality Test (Granger, C. 1969). We use three indicators of the market which are market volatility, market return and β, as market direction, to investigate the relationship between herd behavior and them. Our data are monthly time series which are used and obtained from state-space analysis. To employ Granger causality test, the series need to be stationary. We present unit-root tests in Table 16 by using Augmented Dickey Fuller Unit Root Test. The results indicate that all series are stationary.

Table 16. Unit root tests

Variable	Test Statistic	p-value
h_{mt}	-4.681	(0.000)***
σ_{mt}	-8.285	(0.000)***
r_{mt}	-15.324	(0.000)***
β_{mt}	-15.636	(0.000)***

*** The coefficient is significant at the 1% level.

In the Table 16, h_{mt} represent herd behavior, σ_{mt} is monthly volatility, r_{mt} is monthly market return and β_{mt} is monthly market direction.

While choosing lag structure, we use the selection criteria AIC (Akaike information criteria) and SIC (Schwarz information criteria). AIC and SIC are mostly used to determine the lag degree, so we use what they offered. Up to 13 lag are investigated and they suggest one lag order for all variables.[14] So, we use one lag of the variables to estimate vector autoregression model by the following equation;

$$y_t = \alpha + \sum_{i=1}^{d} \phi_i y_{t-i} + \varepsilon_t \tag{4.28}$$

where y_t is a vector of the dependent variables, ϕ_i is matrix of autoregressive coefficients, d is number of lagged and ε_t is vector of error terms.

Table 17. Results of Granger Causality Test

Variable	Estimate	p-value
volatility → herd behavior	36.295	(0.000)***
herd behavior → volatility	0.006	0.940
return → herd behavior	18.266	(0.000)***
herd behavior → return	1.396	0.237
market direction → herd behavior	0.000	1.000
herd behavior → market direction	3.747	(0.053)*

* The coefficient is significant at the 10% level

*** The coefficient is significant at the 1% level.

After these, we set Granger Causality Test for two way causality with one lagged variables. Estimates are shown in Table 17. The results confirm strongly that market volatility causes herd behavior in the Turkey stock market but herd behavior cannot explain market volatility. When we look at the relation between market returns and herding, it can be said market returns explain herding but there is no evidence that herding cause market return. Finally, to examine the relationship between herding and market direction, the results state that herd behavior can be caused market direction.

[14] The selection order criteria tables are shown in Appendix.

6.5. Discussion

After lots of analysis, we can conclude that investors who trade in Turkey stock market tend to ignore their own decisions and exhibit herd behavior. Besides, we can also say herd behavior is persistent under bear and bull market conditions. When we compare our results with the studies which ours based on, it can be said that some of our findings are consistent with the previous ones, some are not.

First of all, we employed the Christie and Huang (1995) method. CH use cross-sectional standard deviations (CSSD) of stock returns to measure herding. They find dispersion is higher around the market return during large price movements in U.S. stock market, evidence against herding. CH also replicate their analysis to test for the robustness of their results with cross-sectional absolute deviations (CSAD) and they conclude the same results as the previous. However, our results are not completely consistent with CH's findings. We discover a decrease in the dispersion which is an indicator of herding during the period of market stress by using CSSD. On the other hand, when we use CSAD of stock returns, we determine that there is a decrease in the dispersion for down market but there is no evidence of any decline in the dispersion for up market during the large price movements. So, we can conclude, although there is evidence of herd behavior for down market, investors do not tend to herd in up market for Turkey stock market.

In the second part of our study, we use nonlinearity as in Chang at al. (2000). Their method is extended form CH method and they investigate herding in US, Hong Kong, Japan, Taiwan and South Korea financial markets. Their result for U.S market is consistent with CH results. Also, they don't find evidence about herd behavior in Hong Kong market though they find significant evidence of herding in South Korea and Taiwan markets (two emerging markets in their sample) for both up and down markets, and some partial evidence in Japan for down market. As we look at our results by using this approach, the results support the presence of herd behavior in up and down markets for Turkey stock market. Therefore, we can conclude that our results are consistent with CCK which is about South Korea and Taiwan markets because Turkey is also an emerging market. In addition, this can be evidence that due to lack of accurate information in emerging financial markets, investors may tend to focus on more macroeconomic information.

The third method we applied is quantile regression like in Tan et al. (2010). They use Shanghai and Shenzhen markets for A shares and B shares to examine herd behavior. If we look at their results for whole market, we can see that A-share and B-share investors herd conditional on the dispersions of returns in the lower quantiles. Also, they note that, B share investors regularly present herd behavior in the quantiles from the 10% to 50% levels on days when stock market returns are up. Moreover, if we interpret another study by using quantile regression which is done by Zhou and Anderson (2011), herding occurs only in the high quantiles (75% or 90%) of the distribution of return dispersion for the whole period in U.S. REIT market. Our results indicate that investors regularly present herd behavior in the quantiles from the 10% to 75% levels and some partial evidence of herding for 90% quantile.

Our final method to capture herding is Hwang and Salmon (2004) state-space model. They find herd behavior exists for the overall U.S. and South Korean market and it is persistent independently from and given market conditions as expressed in return volatility and market return. So, we find a significant and persistent herd behavior for Turkey stock market as in Hwang and Salmon (2004). However, when we include the market return in our analysis, we don't find any significant evidence between market return and herding.

Finally, we wonder what may cause herding and employ Granger Causality test for market volatility, market return and β as market direction to investigate the relationship between them and herd behavior. The results show us market volatility and market return may cause herding. In addition, herd behavior may cause market direction.

Chapter 7. Conclusion

In this study, we examine market wide herd behavior in Turkey stock market BIST. We use daily stock prices of 499 firms that are listed in the period from 2 January 1991 to 6 May 2016 and follow most commonly used methods which are ordinary least squares, quantile regression, state-space analysis to investigate herding.

First, we employ dummy variables regression test which based on cross-sectional standard deviation by developed Christie and Huang (1995) during the period of market stress. Our results indicate that during periods of extreme price movements, there is a decrease in return dispersion for up and down markets, hence providing evidence the existence of herd behavior. Also, we utilize cross-sectional absolute deviation to test the robustness of the results like in CH. The results have some differences from previous for up markets. While we use absolute term to measure herd behavior, the results show that although herding is still valid in down market during the period of market stress, we are unable to find evidence of herding when the market is up.

Another method which we applied is developed with including nonlinearity into the relation between the return dispersion and the market by Chang et al. (2000). With this approach, while we examine herd behavior overall the market without any market stress criteria, we find significant evidence about herding. Moreover, when we separate the market as up and down and replicate the test for herding, we see that herd behavior occurs in both rising and falling markets in Turkey stock market. These findings suggest that investors who trade in Turkey stock market, display herd behavior.

We elaborate our analysis to detect herd behavior with quantile regression model which we is built on return dispersions and estimations are made by using sample points conditional on a specific quantile. We use cross-sectional absolute deviations as return dispersions and the quantiles 10%, 25%, 50%, 75% and 90%. Based on the market, herd behavior is found to be present in the quantiles from 10% to 75% and some partial evidence in the quantile 90%. While we consider herding under the rising and falling markets conditions, we can conclude investors display herd behavior for all quantiles in the falling market. However, when we examine herding under rising market conditions, the results show that herd behavior exists till the quantile 90%. In the highest quantile, investors do not display herd behavior for up market. These findings indicate that, investors do not tend to herd only when the market is under the extreme conditions, but also it can be present when the market is quiet. Additionally, we also test the asymmetry of herd behavior for up and down markets in nonlinearity regression and quantile regression models. For all of them, we are unable to capture an asymmetric behavior which means that we can assume investors response to good and bad economic news symmetrically for both up and down markets in the Turkey stock market.

Additionally, to check to robustness of herding behavior by using the data after 2000, we repeat the cross-sectional analyses for herding. First, we cannot find any significant evidence of herding for extreme price movement days in the market with the CH method. Second, when we use the Chang et al. (2000) method and the results are consistent with our previous findings. Finally, with the quantile regression method, we find herd behavior for the whole market in the quantiles from 10% to 75% but do not find evidence of herding in the quantile 90%. Then, we reexamine the market as up and down markets and the results are consistent with the prior findings for the down market in all the quantiles. However, there is no longer herd behavior in the quantiles from 50% to 90% in the up market. These differences may be caused from the development of the market and the increasing number of individual investors.

The next step to detect herding in our study is done with state-space method which is developed by Hwang and Salmon (2004). After the analysis with state-space approach, the results indicate us herding remains significant and persistent. Our findings also suggest us, herding seems to increase with financial crisis or some political events such as 2001 and 2013. In other words, when there is a decrease in return dispersion, herd behavior increases or when there is an increase in return dispersion, herding decreases. As an example, we find herd behavior is at highest level in Turkey during the economic crisis of 2001 while return dispersion is at lowest level. Besides, when we look at "Gezi Park Protests" which happened in early of May 2016, it can be seen easily that herd behavior increases after this. Also, herding is at a high level at August 2013 which is associated with "Ergenekon

Trials". Furthermore, while we include volatility into our study, it has a significant and negative effect on return dispersion that means when the market becomes riskier return dispersion decreases or becomes less risky, the return dispersion increases.

In addition to these mentioned methods, we also examine causality effects on herding and the results can be seen as an indicator that the changes of volatility and return of previous days may be an explanation of herd behavior. Consequently, our study results consistently show that investors in Turkey display herd behavior towards the market whatever the market conditions. This suggests that there is at least one investor who suppresses her/his private information and imitates the actions of the others.

REFERENCES

Al-Shboul, M. (2013). *An Examination of Herd Behavior in the Jordanian Equity Market*. International Journal of Economics and Finance, 5 (1), 234-249.

Asch, S. (1955). *Options and Social Pressure*. Scientific American, 193 (5), 31-35.

Avery, C., and Zemsky, P., (1998). *Multidimensional uncertainty and herd behavior in financial markets*. The American Economic Review, 88 (4), 724-748.

Banerjee, A.V. (1992). *A simple model of herd behavior*. The Quarterly Journal of Economics, 108 (3), 797-817.

Barnes, M., and Hughes, A. W. (2002).*A quantile regression analysis of the cross section of stock market returns*. Working Paper, Federal Reserve Bank of Boston.

Bikhchandani, S., Hirshleifer D. and Welch I. (1992). *A Theory of Fads, Fashion, Custom and Cultural Change As Informational Cascades*. Journal of Political Economy, 100, 992-1027.

Bikhchandani, S., and Sharma, S. (2001). *Herd behavior in financial markets*. IMF Staff Papers, 47, 279–310.

Bekaert, G., and Wu, G. (2000). *Asymmetric volatility and risk in equity markets*. Review of Financial Studies, 13, 1–42.

Botsvadze, I. (2013). *Herd Behavior in Equity Markets - The International Evidence*. Journal of Business, 2 (2), 41-46.

Chang, E.C., Cheng, J.W. and Khorana, A. (2000). *An examination of herd behavior in equity markets: An international perspective.* Journal of Banking and Finance, 24 (10), 1651-1679.

Chiang, T.C., Li, J. and Tan, L. (2010). *Empirical investigation of herding behavior in Chinese stock markets: Evidence from quantile regression analysis*. Global Finance Journal, 21 (1), 111-124.

Chiang, T.C. and Zheng, D. (2010). *An empirical analysis of herd behavior in global stock markets.* Journal of Banking and Finance, 34 (8), 1911-1921.

Christie, W. G., and Huang, R. D. (1995). *Following the pied piper: do individual returns herd around the market?* Financial Analysts Journal, 51, 31–37.

Commandeur, J. J. F., Koopman, S.J. and Ooms, M. (2011).*Statistical Software for State Space Methods.*Journal of Statistical Software, 41 (1), 1-18.

De Bondt, W., Muradoglu, G., Shefrin, H., and Staikouras, S.K. (2008).*Behavioral Finance: Quo Vadis?.*Journal of Applied Finance, 18 (2), 7-21.

Demirer, R., and Kutan, A. M. (2006). *Does herding behavior exist in Chinese stock markets?* Journal of International Financial Markets, Institutions and Money, 16, 123–142.

Demirer, R., Kutan, A. M. and Chen, C. (2010). *Do investors herd in emerging stock markets?: Evidence from the Taiwanese market.* Journal of Economic Behavior and Organization, 76 (2), 283-295.

Devenow, A. and Welch I. (1996). *Rational Herding in Financial Economics.* European Economic Review, 40, 603-615.

Duffee, G. R. (2000). *Asymmetric cross-sectional dispersion in stock returns: Evidence and implications.* Berkeley: Working Paper U.C.

Drukker, D. M. and Gates, R. B. (2011). *State Space Methods in Stata.* Journal of Statistical Software, 41 (10), 1-25.

Economou, F., Kostakis, A. and Philippas, N. (2011). *Cross-country effects in herding behaviour Evidence from four south European markets*. International Financial Markets, Institutions and Money, 21, 443-460.

Fama, Eugene F. and French Kenneth, R. (1993).*Common risk factors in the returns on stocks and bonds*. Journal of Financial Economics, 33, 3-56.

Filip, A. M., Pece, A. M. and Pochea, M. M. (2014). *An Empirical Investigation of Herding Behavior in CEE Stock Markets under the Global Financial Crisis.*ProcediaEconomicsand Finance, 25, 354–361.

Gleason, K. C., Mathur, I. and Peterson, M. A. (2003). *Herding Behavior in European Futures Markets.* Finance Letters, 1, 5-8.

Gleason, K.C., Mathur, I. and Peterson, M.A. (2004). *Analysis of intraday herding behavior among the sector ETFs*. Journal of Empirical Finance, 11, 681-94.

Granger, C. (1969). *Investigating Causal Relations by Econometric Models and Cross-Spectral Methods*. Econometrica, 37, 424–438.

Grinblatt, M., Titman, S. and Wermers, R. (1995).*Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior.*American Economic Review, 85, 1088–1105.

Hachicha, N., Bouri, A. and Chakroun, H. (2007). *The Herding Behaviour and the Measurement Problems Proposition of Dynamic Measure*. Journal of Business and Policy Research, 3 (2), 44-63.

Henker, J., Henker, T. and Mitsios, A. (2006). *Do investors herd intraday in Australian equities.* International Journal of Managerial Finance, 2 (3), 196–219.

Hwang, S. and Salmon, M. (2001). *A New Measure of Herding and Empirical Evidence.* Financial Econometrics Research Centre, Working Paper No WP01-12, City University Business School.

Hwang, S., and Salmon, M. (2004). *Market stress and herding*. Journal of Empirical Finance, 11, 585–616.

Hwang, S., and Salmon, M. (2005). *Measuring Sentiment and Herding in Financial Markets.*Faculty of Finance, Cass Business School.

Hirshleifer, D. and Teoh, S. H. (2003). *Herd behaviour and cascading in capital markets: A review and synthesis.* European Financial Management, 9 (1), 25-66.

Kandır S. Y. (2006) *Türkiye'de yatırımcı duyarlılığının hisse senedi getirileri üzerindeki etkisi*. PhD Thesis. Cukurova University.

Kapusuzoglu, A. (2011). *Herding in the Istanbul Stock Exchange (ISE) A case of behavioral finance.* African Journal of Business Management, 5 (27), 11210-11218.

Khan, H., S. Hassairi and Viviani J. L. (2011). *Herd behavior and market stress: The case of four European countries*. International Business Research, 4, 53-67

Koenker, R. W. (2005). *Quantile regression*. Cambridge University Press.

Koenker, R. W., and Bassett, G., Jr. (1978). Regression quantiles.Econometrica, 46, 33–50.

Kremer, S. and Nautz, D. (2013). *Causes and consequences of short-term institutional herding*. Journal of Banking & Finance, 37, 1676–1686

Lakonishok, J., Shleifer A. and Vishny W. (1992). *The impact of institutional trading on stock prices.* Journal of Financial Economics, 32, 23–44

Laih, Y. W and Liau, Y. S. (2013). *Herding Behavior during the Subprime Mortgage Crisis: Evidence from Six Asia-Pacific Stock Markets.* International Journal of Economics and Finance, 5 (7). 71-84.

Lao, P. and Singh, H. (2011). *Herding behaviour in the Chinese and Indian stock markets.* Journal of Asian Economics, 22, 495–506.

Le, U. M. and Truong, H. N. (2014). *An Exploratory Study of Herd Behaviour in Vietnamese Stock Market: A New Method*. Asian Journal of Finance & Accounting, 6 (1), 464-475.

Lindhe, E. (2012). *Herd Behavior in Stock Markets A Nordic Study*. Master Thesis. Lunds University.

Malik, S. U. and Elahi, M.A. (2014). *Analysis of Herd Behavior Using Quantile Regression Evidence from Karachi Stock Exchange (KSE).* MPRA Paper No. 55322, posted 16.

Messis, P. and Zapranis, A. (2014). *Herding behavior and volatility in the Athens Stock Exchange.* The Journal of Risk Finance, 15 (5), 572-590.

Pop, R. E. (2012). *Herd behavior towards the market index evidence from Romanian stock exchange.* MPRA Paper, No. 51595, posted 26.

Poshakwale, S. and Mandal, A. (2014). *Investor Behaviour and Herding Evidence from the National Stock Exchange in India.* Journal of Emerging Market Finance, 13 (2), 197–216.

Saastamoinen, J. (2008). *Quantile Regression Analysis of Dispersion of Stock Returns-Evidence of Herd behavior*. *Discussion Papers,* No. 57. University of Joensuu, Economics.

Seetharam, Y. and Britten, J. (2013). *An Analysis of Herding Behaviour during Market Cycles in South Africa.* Journal of Economics and Behavioral Studies, 5 (2), 89-98.

Scharfstein, D. S. and Stein, J. C. (1990). *Herd Behavior and Investment*. The American Economic Review, 80 (3), 465-479.

Shiller, R. J. (1995). *Conversation, Information, and Herd Behavior*. The American Economic Review 85 (2), 181-185

Shiller, R. J. (2003). *From Efficient Markets Theory to Behavioral Finance*. The Journal of Economic Perspectives, 17 (1), 83-104.

Schmeling, M. (2009). *Investor sentiment and stock returns: Some international evidence.* Journal of Empirical Finance, 16, 394–408

Schwert, G. W., 1989. *Why does stock market volatility change over time?.* Journal of Finance 44, 1115–1153.

Solakoglu, M. N. and Demir, N. (2014). *Sentimental herding in Borsa Istanbul informed versus uninformed*. Applied Economics Letters, 21 (14), 965-968.

StataCorp (2012a). *Stata Progamming Reference Manual, Release 12*. Stata Press, College Station, Texas.

StataCorp (2012b). *Stata Structrual Equation Modeling Reference Manual, Release 12*. Stata Press, College Station, Texas.

Tan, L., Chiang, T. C., Mason, J. R. and Nelling, E. (2008). *Herding behavior in Chinese stock markets: An examination of A and B shares*. Pacific-Basin Finance Journal, 16, 61–77.

Trenca, I., Pece, A. M. and Mihut, I. S. (2015). *Herd behaviour of institutional and individual investors in thecontext of economicgovernance: evidence from Romanian* *stock market*. Review of Economic Studies and Research Virgil Madgearu, 1, 177-190.

Trueman, B., (1994). *Analyst Forecast and Herding Behavior*. Review of Financial Studies, 7, 97-124.

Welch, I. (1992). *Sequential sales, learning and cascades.*Journal of Finance, 47, 695-732.

Wermers, R. (1999). *Mutual fund herding and the impact on stock prices*.Journal of Finance, 54, 581-622

Wiley, S. (2005). *Fund Manager Herding A Test of the Accuracy of Empirical Results Using U.K. Data.*The Journal of Business, 78 (1), 381-403.

Zhou, J. and Anderson, R. I. (2011). *An empirical investigation of herding behavior in the U.S. REIT market*. Journal of Real Estate Finance and Economics, 47, 83–108.

Websites:

https://en.wikipedia.org/wiki/Asch_conformity_experiments

http://www.moneycrashers.com/dot-com-bubble-burst/

https://en.wikipedia.org/wiki/Dot-com_bubble

http://www.investopedia.com/terms/d/dotcom-bubble.asp

APPENDIX A: Tables of Data

Table A1. Descriptive statistics of 499 stock returns' observations which are traded in the BIST

Stock	Time Period	Number of Observations	Mean	S.D.	Min	Max
ABANA	1992-2008	4018	0.0009	0.0693	-0.6931	0.6931
ACIBD	2000-2012	3086	0.0013	0.0306	-0.1942	0.1892
ACSEL	2012-2016	959	0.0001	0.0335	-0.2040	0.1957
ADANA	1996-2016	5041	0.0013	0.0440	-0.6931	0.6931
ADBGR	1997-2016	4822	0.0013	0.0470	-0.9383	0.8938
ADEL	1996-2016	4967	0.0013	0.0430	-0.4055	0.4055
ADESE	2011-2016	1130	0.0007	0.0253	-0.1964	0.1444
ADNAC	1997-2016	4711	0.0009	0.0662	-0.6931	0.6931
AEFES	2000-2016	3960	0.0007	0.0271	-0.2364	0.2305
AFMAS	2004-2014	2379	0.0005	0.0297	-0.1446	0.1854
AFYON	1995-2016	5266	0.0012	0.0633	-0.6931	1.7812
AGYO	2002-2016	3570	0.0004	0.0283	-0.1620	0.1699
AKALT	1992-2013	5127	0.0011	0.0471	-0.6931	0.6931
AKBNK	1994-2016	5551	0.0012	0.0403	-0.4055	0.6931
AKCNS	1996-2016	4892	0.0011	0.0324	-0.1823	0.2231
AKENR	2000-2016	3969	0.0000	0.0275	-0.1876	0.1892
AKFEN	2010-2016	1500	0.0002	0.0208	-0.1911	0.1823
AKFGY	2011-2016	1253	-0.0003	0.0215	-0.1426	0.1342
AKGRT	1997-2016	4831	0.0011	0.0506	-0.6931	0.6931
AKGUV	2012-2016	963	-0.0003	0.0273	-0.1864	0.1818
AKIPD	1993-2009	4016	0.0007	0.0437	-0.2231	0.2231
AKMGY	2005-2016	2782	0.0003	0.0240	-0.1538	0.1823
AKPAZ	2013-2016	725	-0.0023	0.0299	-0.2007	0.1823
AKSA	1992-2016	5943	0.0011	0.0490	-0.6931	0.6931
AKSEL	2011-2016	1196	-0.0008	0.0407	-0.2178	0.1975
AKSEN	2010-2016	1498	-0.0004	0.0204	-0.1579	0.1054
AKSGY	1993-2016	5757	0.0010	0.0453	-0.4055	0.6931
AKSUE	2000-2016	4093	0.0005	0.0328	-0.2235	0.2200
ALARK	1993-2016	5683	0.0010	0.0484	-0.6931	0.6931
ALBRK	2007-2016	2225	0.0001	0.0197	-0.1162	0.1257
ALCAR	1992-2016	5957	0.0014	0.0385	-0.4055	0.6931
ALCTL	1992-2016	5982	0.0009	0.0501	-0.6931	0.6931
ALGYO	1997-2016	4830	0.0009	0.0300	-0.1744	0.2007
ALKA	2000-2016	3886	0.0002	0.0309	-0.2644	0.2136
ALKIM	2000-2016	4054	0.0006	0.0288	-0.2336	0.1942
ALNTF	1995-2015	4997	0.0008	0.0578	-0.6931	0.6931
ALYAG	2000-2016	3992	-0.0004	0.0367	-0.2311	0.2097
ANACM	1994-2016	5450	0.0010	0.0552	-0.6931	0.6931

Stock	Time Period	Number of Observations	Mean	S.D.	Min	Max
ANALE	2010-2016	1480	-0.0004	0.0217	-0.1495	0.1574
ANELT	2005-2016	2677	-0.0001	0.0255	-0.2212	0.1833
ANHYT	2000-2016	4059	0.0006	0.0323	-0.2076	0.2076
ANSA	2005-2016	2756	-0.0003	0.0376	-0.2231	0.1934
ANSGR	1996-2016	4932	0.0010	0.0589	-0.6931	0.6931
ARAT	1997-2007	2356	-0.0006	0.0478	-0.2429	0.2231
ARBUL	2014-2016	463	-0.0038	0.0431	-0.2215	0.1843
ARCLK	1993-2016	5796	0.0013	0.0458	-0.4055	0.6931
ARENA	2000-2016	3886	0.0004	0.0324	-0.1924	0.2231
ARFYO	1996-2014	4519	0.0009	0.0568	-0.6931	0.6931
ARMDA	2006-2016	2488	0.0009	0.0296	-0.1542	0.1819
ARSAN	1998-2016	4458	0.0004	0.0391	-0.2877	0.2348
ARTI	2006-2016	2491	-0.0005	0.0395	-0.2271	0.1883
ARTOG	2012-2015	597	-0.0025	0.0646	-0.8602	0.1939
ASCEL	2012-2016	930	-0.0045	0.0513	-0.2167	0.1967
ASELS	1995-2016	5265	0.0014	0.0438	-0.4055	0.6931
ASLAN	1994-2016	5481	0.0015	0.0798	-0.6931	0.6931
ASUZU	1997-2016	4763	0.0008	0.0345	-0.2173	0.1851
ASYAB	2006-2016	2480	-0.0003	0.0309	-0.2252	0.2031
ATAC	2011-2014	744	-0.0035	0.0403	-0.2167	0.1611
ATAGY	1997-2016	4627	0.0009	0.0390	-0.2305	0.2683
ATEKS	1996-2016	5000	0.0009	0.0372	-0.1942	0.2053
ATLAS	1994-2016	5441	0.0008	0.0623	-0.6931	0.6931
ATPET	2012-2016	892	-0.0006	0.0372	-0.2224	0.1853
ATSYH	1995-2016	5233	0.0004	0.0444	-0.4055	0.4055
AVGYO	1996-2016	4939	0.0006	0.0500	-0.2877	0.4055
AVHOL	2012-2016	856	-0.0004	0.0387	-0.2231	0.1711
AVISA	2014-2016	373	0.0009	0.0162	-0.0605	0.1109
AVOD	2011-2016	1111	-0.0003	0.0272	-0.2045	0.1466
AVTUR	2007-2016	2264	0.0002	0.0415	-0.2215	0.2052
AYCES	1994-2016	5439	0.0011	0.0469	-0.6931	0.6931
AYEN	2000-2016	3970	0.0004	0.0290	-0.2513	0.1978
AYES	2013-2016	797	-0.0019	0.0488	-0.2174	0.1953
AYGAZ	1994-2016	5454	0.0013	0.0394	-0.4055	0.6931
BAGFS	1993-2016	5763	0.0013	0.0556	-0.6931	0.6931
BAKAB	1998-2016	4468	0.0006	0.0335	-0.2877	0.2513
BAKAN	2013-2016	724	-0.0016	0.0460	-0.2249	0.1948
BALAT	2012-2016	926	-0.0060	0.0463	-0.2190	0.2033
BANVT	1994-2016	5394	0.0010	0.0659	-0.6931	0.6931
BASCM	2012-2016	926	-0.0011	0.0334	-0.2164	0.1964
BERDN	1997-2013	4049	-0.0005	0.0406	-0.1766	0.2128
BEYAZ	2012-2016	1029	-0.0002	0.0405	-0.2141	0.1837
BFREN	1994-2016	5576	0.0012	0.0560	-1.9394	1.9312

Stock	Time Period	Number of Observations	Mean	S.D.	Min	Max
BIMAS	2005-2016	2718	0.0012	0.0235	-0.1665	0.2172
BISAS	1996-2016	4827	0.0000	0.0440	-0.2666	0.2231
BIZIM	2011-2016	1322	-0.0003	0.0188	-0.1455	0.0789
BJKAS	2002-2016	3566	0.0005	0.0419	-0.4082	1.2176
BLCYT	2011-2016	1249	-0.0003	0.0274	-0.2113	0.1792
BMEKS	2011-2016	1272	-0.0004	0.0180	-0.0953	0.1233
BMELK	2014-2016	476	-0.0018	0.0293	-0.2128	0.1752
BNKTRF	2009-2016	1678	0.0002	0.0202	-0.1103	0.0997
BNTAS	2015-2016	244	-0.0012	0.0206	-0.0889	0.1823
BOLUC	1994-2016	5418	0.0012	0.0407	-0.4055	0.6931
BOSSA	1995-2016	5172	0.0009	0.0512	-0.4055	0.4055
BOYNR	1996-2016	4921	0.0007	0.0371	-0.2513	0.2011
BOYP	1992-2016	5985	0.0015	0.0454	-0.4055	0.6931
BRISA	1994-2016	5429	0.0012	0.0571	-0.6931	0.6931
BRKO	2009-2016	1764	-0.0003	0.0265	-0.1335	0.1978
BRKSN	2011-2016	1321	0.0002	0.0402	-0.2162	0.1942
BRMEN	1996-2016	4933	0.0002	0.0371	-0.2412	0.2231
BRSAN	1994-2016	5409	0.0012	0.0653	-0.6931	0.6931
BRYAT	1996-2016	4866	0.0012	0.0357	-0.2209	0.2041
BSHEV	1991-2014	5778	0.0017	0.0529	-0.6931	0.6931
BSOKE	2000-2016	4015	0.0004	0.0275	-0.1671	0.1719
BTCIM	1995-2016	5275	0.0009	0.0335	-0.2231	0.2231
BUCIM	1993-2016	5640	0.0011	0.0461	-0.6931	0.6931
BURCE	1994-2016	5477	0.0011	0.0499	-0.4055	0.6931
BURVA	2004-2016	3012	-0.0001	0.0332	-0.1964	0.1946
BYSAN	1997-2008	2437	-0.0003	0.0568	-0.2985	0.6190
CBSBO	1995-2013	4637	0.0001	0.0441	-0.2364	0.2063
CCOLA	2006-2016	2511	0.0006	0.0243	-0.1431	0.1670
CELHA	1992-2016	5858	0.0009	0.0525	-0.4055	0.6931
CEMAS	2010-2016	1468	-0.0006	0.0335	-0.1883	0.1950
CEMTS	1995-2016	5330	0.0010	0.0561	-0.6931	0.6931
CIMSA	1993-2016	5608	0.0013	0.0522	-0.6931	0.6931
CLKHO	2011-2014	805	-0.0018	0.0340	-0.1964	0.1509
CMBTN	1997-2016	4589	0.0007	0.0378	-0.2426	0.2155
CMENT	1992-2016	5872	0.0012	0.0424	-0.6931	0.6931
CMLOJ	1995-2007	3079	0.0016	0.0495	-0.9614	0.2412
COMDO	1993-2016	5796	0.0011	0.0551	-0.6931	0.6931
COSMO	1995-2016	5196	0.0009	0.0510	-0.4055	0.6931
CRDFA	1997-2016	4561	0.0009	0.0678	-0.6931	0.6931
CRFSA	2015-2016	187	-0.0004	0.0273	-0.0773	0.1819
CUSAN	2016-2016	52	0.0096	0.0341	-0.0290	0.1815
CYTAS	1997-2009	3025	0.0009	0.0507	-0.2733	0.2513
DAGHL	1997-2016	4760	0.0007	0.0489	-0.4055	0.4055

Stock	Time Period	Number of Observations	Mean	S.D.	Min	Max
DAGI	2011-2016	1239	0.0002	0.0254	-0.1936	0.1695
DARDL	1994-2016	5309	0.0002	0.0433	-0.2442	0.6341
DENCM	1993-2016	5730	0.0013	0.0561	-0.6931	0.6931
DENGE	2012-2016	941	-0.0002	0.0365	-0.2217	0.1926
DENIZ	2004-2016	2915	0.0006	0.0312	-0.2231	0.2086
DENTA	2000-2014	3463	0.0007	0.0322	-0.2214	0.2513
DERIM	1993-2016	5796	0.0012	0.0586	-0.6931	0.6931
DESA	2004-2016	3019	-0.0002	0.0263	-0.1733	0.1498
DESPC	2010-2016	1363	0.0005	0.0251	-0.1798	0.1748
DEVA	1993-2016	5798	0.0010	0.0561	-0.6931	0.6931
DGATE	2006-2016	2576	0.0008	0.0330	-0.2162	0.1735
DGGYO	1998-2016	4524	0.0008	0.0405	-0.2877	0.2336
DGKLB	1993-2016	5797	0.0008	0.0512	-0.6931	0.6931
DGZTE	1993-2016	5649	0.0007	0.0705	-0.6931	0.6931
DIRIT	2012-2016	922	-0.0031	0.0400	-0.2158	0.1975
DITAS	1993-2016	5795	0.0010	0.0558	-0.6931	0.6931
DJIMTF	2006-2016	2514	0.0002	0.0142	-0.0817	0.0946
DJISTF	2005-2016	2845	0.0005	0.0175	-0.0951	0.1214
DMSAS	1997-2016	4693	0.0006	0.0353	-0.2877	0.2624
DOAS	2004-2016	2990	0.0006	0.0276	-0.1723	0.1283
DOBUR	2000-2016	4041	0.0001	0.0350	-0.2007	0.2472
DOCO	2010-2016	1367	0.0014	0.0166	-0.1372	0.1166
DOGUB	1993-2016	5742	0.0009	0.0603	-0.6931	0.6931
DOHOL	1995-2016	5303	0.0008	0.0584	-0.6931	0.6931
DURDO	1993-2016	5720	0.0010	0.0578	-0.6931	0.6931
DYHOL	1998-2014	4012	0.0001	0.0409	-0.2412	0.2231
DYOBY	1992-2016	5965	0.0009	0.0485	-0.6931	0.6931
DZGYO	1995-2016	5121	0.0008	0.0626	-0.6931	0.6931
ECBYO	1999-2016	4320	0.0007	0.0356	-0.2877	0.2877
ECILC	1995-2016	5293	0.0011	0.0486	-0.6931	0.6931
ECYAP	1995-2015	4947	0.0007	0.0344	-0.2513	0.2513
ECZYT	1994-2016	5473	0.0013	0.0461	-0.6931	0.6931
EDIP	1994-2016	5458	0.0008	0.0516	-0.6931	0.6931
EFES	1998-2006	2194	0.0007	0.0402	-0.2249	0.1895
EGCYH	1998-2016	4453	0.0001	0.0480	-0.3365	0.2877
EGCYO	1995-2016	5269	0.0007	0.0686	-0.6931	0.6931
EGEEN	1992-2016	5962	0.0017	0.0549	-0.6931	0.6931
EGGUB	1994-2016	5524	0.0014	0.0439	-0.4055	0.6931
EGLYO	1999-2016	4240	0.0006	0.0347	-0.2231	0.2231
EGPRO	1995-2016	5253	0.0011	0.0533	-0.6931	0.6931
EGSER	1993-2016	5798	0.0009	0.0413	-0.2877	0.4055
EGYO	1998-2013	3453	-0.0004	0.0433	-0.1929	0.2624
EKGYO	2010-2016	1354	0.0004	0.0220	-0.1347	0.1135

Stock	Time Period	Number of Observations	Mean	S.D.	Min	Max
EKIZ	2010-2016	1455	-0.0017	0.0374	-0.2113	0.1974
EMKEL	1998-2016	4489	0.0000	0.0389	-0.2205	0.2231
EMNIS	1995-2016	5088	0.0005	0.0400	-0.2303	0.2446
EMPAS	1994-2000	1479	0.0002	0.0628	-0.2348	0.6600
EMSAN	1993-2000	1522	0.0006	0.0627	-0.2265	0.6806
ENKAI	1997-2016	4828	0.0013	0.0467	-0.6931	0.6931
EPLAS	1994-2016	5467	0.0007	0.0480	-0.6931	0.6931
ERBOS	1995-2016	5256	0.0010	0.0346	-0.2069	0.2502
EREGL	1995-2016	5302	0.0012	0.0541	-0.6931	0.6931
ERICO	2011-2014	791	-0.0028	0.0447	-0.2178	0.2134
ERSU	2000-2016	4034	0.0001	0.0345	-0.2397	0.2007
ESCOM	2000-2016	3959	0.0000	0.0361	-0.3298	0.1993
ESEMS	1995-2016	5214	0.0000	0.0445	-0.1946	0.2043
ETILR	2012-2016	953	-0.0004	0.0409	-0.2231	0.1393
ETYAT	2008-2016	2003	-0.0004	0.0331	-0.2215	0.1962
EUHOL	2010-2016	1477	-0.0008	0.0424	-0.2351	0.1934
EUKYO	2011-2016	1186	-0.0006	0.0371	-0.2154	0.1761
EUYO	2006-2016	2481	-0.0003	0.0319	-0.2007	0.1975
FBISTF	2007-2016	2144	0.0004	0.0029	-0.0218	0.0171
FENER	2004-2016	3072	0.0005	0.0278	-0.2153	0.2012
FENIS	1994-2016	5438	0.0006	0.0571	-0.6931	0.6931
FFKRL	1995-2016	5291	0.0011	0.0456	-0.4055	0.6931
FINBN	1996-2016	4893	0.0013	0.0487	-0.4055	0.6931
FISCTR	2012-2016	487	-0.0004	0.0407	-0.3555	0.3145
FLAP	2012-2016	965	-0.0016	0.0386	-0.2128	0.1677
FMIZP	1993-2016	5748	0.0013	0.0620	-0.6931	0.6931
FNSYO	1996-2014	4627	0.0007	0.0405	-0.2877	0.2877
FONSY	2006-2016	2381	-0.0005	0.0282	-0.2219	0.1957
FORTS	1996-2011	3731	0.0014	0.0509	-0.4055	0.6931
FRIGO	1995-2016	5239	0.0001	0.0388	-0.2384	0.2079
FROTO	1994-2016	5456	0.0015	0.0554	-0.6931	0.6931
FVORI	2000-2015	3664	-0.0004	0.0428	-0.2322	0.2136
FYKBNK	2012-2016	355	-0.0007	0.0637	-0.5819	0.4986
GARAN	1994-2016	5451	0.0012	0.0466	-0.6931	0.6931
GARFA	1994-2016	5469	0.0010	0.0836	-0.6931	0.6931
GDKGS	2006-2016	2326	0.0005	0.0261	-0.1655	0.2059
GEDIK	2010-2016	1405	0.0006	0.0152	-0.0709	0.1823
GEDIZ	1996-2016	4957	0.0003	0.0415	-0.2231	0.2384
GEDZA	2014-2016	575	-0.0003	0.0305	-0.1328	0.1792
GENTS	1995-2016	5263	0.0009	0.0504	-0.6931	0.6931
GENYH	1995-2016	5264	0.0005	0.0498	-0.2513	0.2877
GEREL	2003-2016	3261	0.0002	0.0287	-0.2382	0.1978
GIMA	1993-2006	3168	0.0018	0.0806	-1.0986	1.0986

Stock	Time Period	Number of Observations	Mean	S.D.	Min	Max
GLBMD	2011-2016	1212	-0.0010	0.0283	-0.2029	0.1851
GLDTRF	2006-2016	2414	0.0005	0.0125	-0.0926	0.0892
GLRYH	2006-2016	2501	-0.0002	0.0295	-0.2108	0.1823
GLYHO	1995-2016	5231	0.0002	0.0401	-0.2549	0.1961
GMSTR	2012-2016	1007	-0.0001	0.0159	-0.1220	0.0970
GNPWR	2005-2016	2704	-0.0004	0.0403	-0.1961	0.2091
GOLDPF	2010-2016	1447	0.0005	0.0110	-0.1013	0.0551
GOLDS	2000-2013	3320	-0.0004	0.0340	-0.2143	0.2053
GOLTS	1995-2016	5174	0.0012	0.0373	-0.2412	0.4289
GOODY	1992-2016	5969	0.0014	0.0372	-0.4055	0.4055
GOZDE	2010-2016	1580	0.0010	0.0301	-0.1909	0.1961
GRNYO	1997-2016	4706	0.0009	0.0585	-0.6931	0.6931
GRUND	1992-2009	4158	0.0010	0.0571	-0.6931	0.6931
GSDDE	1995-2016	5294	0.0007	0.0540	-0.6931	0.6931
GSDHO	1999-2016	4129	0.0002	0.0386	-0.2296	0.2126
GSRAY	2002-2016	3566	0.0003	0.0295	-0.2213	0.1765
GUBRF	1994-2016	5352	0.0012	0.0655	-0.6931	0.6931
GUSGR	1994-2016	5354	0.0009	0.0546	-0.6931	0.6931
GYHOL	1999-2016	4114	0.0007	0.0321	-0.2132	0.2076
HALKB	2007-2016	2254	0.0002	0.0273	-0.1317	0.1869
HALKS	2012-2016	983	0.0014	0.0525	-0.5764	0.4494
HATEK	2011-2016	1335	-0.0002	0.0340	-0.2141	0.1958
HDFGS	2015-2016	316	0.0002	0.0555	-0.2219	0.1823
HEKTS	1995-2016	5296	0.0011	0.0438	-0.4055	0.6931
HITIT	2012-2015	753	-0.0002	0.0356	-0.2090	0.1644
HLGYO	2013-2016	802	-0.0002	0.0161	-0.1310	0.0862
HURGZ	1996-2016	5068	0.0008	0.0425	-0.4055	0.6931
HZNDR	1995-2016	5048	0.0009	0.0414	-0.2877	0.2412
ICBCT	1994-2016	5429	0.0010	0.0529	-0.6931	0.6931
IDAS	1998-2016	4460	-0.0002	0.0394	-0.2231	0.1983
IDGYO	2010-2016	1469	0.0000	0.0385	-0.2097	0.1942
IEYHO	1998-2016	4430	-0.0004	0.0436	-0.2246	0.3353
IHEVA	1996-2016	4647	0.0005	0.0469	-0.2513	0.8938
IHGZT	2010-2016	1482	-0.0008	0.0330	-0.1911	0.1812
IHLAS	1994-2016	5295	0.0002	0.0498	-0.6931	0.7133
IHMAD	1992-2016	5988	0.0007	0.0672	-0.6931	0.6931
IHYAY	2010-2016	1382	-0.0015	0.0314	-0.1632	0.1949
INDES	2004-2016	2985	0.0007	0.0222	-0.1493	0.1560
INFO	2011-2016	1148	-0.0005	0.0284	-0.2112	0.1600
INTEM	1992-2016	5969	0.0011	0.0495	-0.6931	0.6931
IPEKE	2000-2016	3973	0.0003	0.0419	-0.2578	0.2007
IS30F	2009-2016	1780	0.0007	0.0160	-0.0931	0.0643
ISATR	1991-2016	2645	0.0023	0.3555	-6.9070	7.0854

Stock	Time Period	Number of Observations	Mean	S.D.	Min	Max
ISBIR	2012-2016	850	-0.0029	0.0403	-0.2144	0.1944
ISBTR	1991-2016	5988	0.0010	0.0379	-0.2126	0.2180
ISCTR	1995-2016	5275	0.0012	0.0436	-0.6931	0.6931
ISDMR	2016-2016	25	0.0083	0.1074	-0.2223	0.1823
ISFIN	2000-2016	4041	0.0007	0.0435	-0.4055	0.4055
ISGSY	2004-2016	2900	0.0003	0.0196	-0.1148	0.1800
ISGYO	1999-2016	4109	0.0005	0.0297	-0.2151	0.1872
ISKUR	2001-2016	1276	0.0018	0.0831	-0.5756	0.5680
ISMEN	2007-2016	2255	0.0002	0.0206	-0.1155	0.1361
IST30F	2009-2016	1780	0.0007	0.0160	-0.0931	0.0643
ISY30F	2007-2016	2250	0.0003	0.0176	-0.0865	0.1199
ISYAT	1997-2016	4816	0.0009	0.0410	-0.2877	0.6931
ISYHO	1994-2014	5061	0.0001	0.0441	-0.2771	0.2364
ITTFH	2010-2016	1596	-0.0008	0.0253	-0.2128	0.1542
IZFAS	2014-2016	460	-0.0008	0.0352	-0.1285	0.1868
IZMDC	1993-2016	5679	0.0010	0.0568	-0.6931	0.6931
IZOCM	1992-2016	5970	0.0013	0.0575	-0.6931	0.6931
IZTAR	2013-2016	625	-0.0006	0.0405	-0.2158	0.3258
JANTS	2012-2016	925	0.0007	0.0284	-0.1797	0.1162
KAPLM	1995-2016	5160	0.0005	0.0411	-0.2336	0.2136
KAREL	2006-2016	2398	0.0001	0.0226	-0.1214	0.1782
KARSN	2000-2016	4062	-0.0002	0.0322	-0.2162	0.2096
KARTN	1992-2016	5971	0.0016	0.0382	-0.4055	0.4055
KATMR	2010-2016	1377	0.0006	0.0315	-0.2137	0.1844
KAVPA	1991-2008	4374	0.0012	0.0648	-0.6931	0.6931
KCHOL	1993-2016	5746	0.0013	0.0593	-0.6931	0.6931
KENT	1992-2016	5974	0.0016	0.0483	-0.6931	0.6931
KERVN	1997-2016	4688	0.0000	0.0457	-0.2412	0.2007
KERVT	1994-2016	5446	0.0010	0.0435	-0.2278	0.5903
KILER	2011-2015	1241	-0.0004	0.0261	-0.1614	0.1959
KIPA	1997-2016	4609	0.0009	0.0322	-0.2231	0.2364
KLGYO	2011-2016	1268	-0.0007	0.0255	-0.1504	0.1823
KLMSN	1997-2016	4673	0.0007	0.0349	-0.2231	0.2097
KLNMA	1992-2016	5979	0.0010	0.0602	-0.6931	0.6931
KNFRT	1996-2016	4973	0.0008	0.0377	-0.1745	0.1921
KOHML	2012-2016	866	-0.0009	0.0295	-0.2127	0.1885
KONYA	1992-2016	5972	0.0015	0.0479	-0.7538	0.7538
KORDS	1994-2016	5517	0.0011	0.0398	-0.6931	0.6931
KOTKS	1993-2006	3304	0.0011	0.0670	-0.6931	0.6931
KOZAA	2003-2016	3318	0.0004	0.0365	-0.1978	0.2048
KOZAL	2010-2016	1566	0.0002	0.0295	-0.2140	0.1438
KPHOL	2005-2016	2628	-0.0005	0.0369	-0.2231	0.1823
KRATL	2012-2016	940	-0.0009	0.0234	-0.2231	0.1857

Stock	Time Period	Number of Observations	Mean	S.D.	Min	Max
KRDMA	1998-2016	4425	0.0006	0.0601	-0.4055	0.4055
KRDMB	1998-2016	4415	0.0007	0.0627	-0.6931	0.6931
KRDMD	1998-2016	4478	0.0006	0.0652	-0.6931	0.6931
KRGYO	2014-2016	503	-0.0002	0.0273	-0.1282	0.1789
KRONT	2011-2016	1242	0.0002	0.0320	-0.1780	0.1999
KRSAN	2012-2016	947	-0.0018	0.0401	-0.1966	0.1772
KRSTL	1997-2016	4647	0.0002	0.0401	-0.3483	0.2257
KRTEK	1994-2016	5358	0.0005	0.0439	-0.4055	0.4055
KSTUR	2014-2016	436	-0.0046	0.0763	-0.2155	0.1950
KUTPO	1993-2016	5680	0.0011	0.0437	-0.6271	0.6931
KUYAS	2012-2016	911	0.0000	0.0411	-0.2168	0.1981
LATEK	2010-2015	1264	-0.0023	0.0370	-0.1655	0.2451
LIDFA	2014-2016	472	0.0001	0.0235	-0.0690	0.1741
LINK	2000-2016	3890	0.0000	0.0392	-0.2350	0.2099
LIOYS	2000-2006	1595	-0.0006	0.0358	-0.2231	0.2059
LKMNH	2011-2016	1324	0.0002	0.0266	-0.1688	0.1785
LOGO	2000-2016	4012	0.0010	0.0331	-0.2076	0.2025
LUKSK	1993-2016	5619	0.0010	0.0454	-0.2877	0.6931
MAALT	1992-2016	5973	0.0010	0.0439	-0.4055	0.4055
MAKTK	1992-2016	5954	0.0004	0.0487	-0.2231	0.2469
MANGO	2010-2015	1234	-0.0020	0.0449	-0.2559	0.2231
MARTI	1994-2016	5424	0.0007	0.0485	-0.4055	0.6931
MCTAS	2012-2016	984	0.0003	0.0213	-0.1231	0.1823
MEGAP	2012-2016	994	-0.0012	0.0369	-0.2002	0.1735
MEGES	1997-2008	2865	0.0003	0.0470	-0.3629	0.1967
MEMSA	1997-2016	4609	-0.0004	0.0460	-0.2513	0.2296
MENBA	2013-2016	715	-0.0004	0.0280	-0.1858	0.1790
MEPET	2011-2016	1201	-0.0005	0.0437	-0.2153	0.1971
MERIT	2012-2016	882	-0.0001	0.0614	-0.2231	0.1965
MERKO	1994-2016	5380	0.0005	0.0379	-0.2318	0.2097
METAL	2006-2016	2483	-0.0002	0.0383	-0.2007	0.1991
METRO	1998-2016	4530	0.0004	0.0383	-0.2624	0.2231
METUR	2002-2016	3461	0.0000	0.0349	-0.2203	0.2016
MGROS	1993-2016	5696	0.0013	0.0440	-0.6931	0.6931
MIPAZ	1994-2016	5551	0.0004	0.0532	-0.6931	0.6931
MMCAS	2011-2016	1107	-0.0009	0.0562	-0.2244	0.1938
MNDRS	2000-2016	3955	0.0001	0.0365	-0.2538	0.2288
MRDIN	1997-2016	4728	0.0013	0.0380	-0.6931	0.6931
MRGYO	2010-2016	1411	-0.0008	0.0270	-0.2025	0.2029
MRHSL	1992-2016	5962	0.0014	0.0436	-0.6931	0.6931
MRTGG	2005-2016	2584	-0.0006	0.0440	-0.2210	0.1936
MUTLU	1994-2015	5115	0.0010	0.0486	-0.5441	0.4055
MZHLD	1997-2016	4606	0.0003	0.0426	-0.2162	0.2274

Stock	Time Period	Number of Observations	Mean	S.D.	Min	Max
NETAS	1993-2016	5778	0.0012	0.0453	-0.4055	0.6931
NIBAS	2012-2016	1047	-0.0013	0.0318	-0.1950	0.1823
NTHOL	1993-2016	5740	0.0010	0.0574	-0.6931	0.6931
NTTUR	1993-2016	5672	0.0009	0.0599	-0.6931	0.6931
NUGYO	1999-2016	4106	0.0006	0.0353	-0.2180	0.2113
NUHCM	2000-2016	4036	0.0005	0.0222	-0.1510	0.1919
ODAS	2013-2016	743	0.0004	0.0271	-0.1362	0.1645
OLMIP	1993-2016	5728	0.0012	0.0456	-0.6931	0.6931
ORGE	2012-2016	999	0.0008	0.0423	-0.2208	0.1853
ORMA	2013-2016	628	-0.0048	0.0657	-0.2164	0.1959
OSMEN	2012-2016	744	0.0004	0.0567	-0.2231	0.1972
OSTIM	2012-2016	993	0.0002	0.0577	-0.5767	0.4495
OTKAR	1995-2016	5251	0.0014	0.0416	-0.2877	0.2877
OYAYO	2007-2016	2266	-0.0001	0.0280	-0.1473	0.1823
OYLUM	2012-2016	1006	-0.0001	0.0351	-0.1972	0.2094
OYSAC	1994-2007	3392	0.0019	0.0667	-0.6931	0.6931
OZBAL	2011-2016	1199	-0.0008	0.0330	-0.2007	0.1995
OZGYO	1995-2016	5294	0.0008	0.0503	-0.4055	0.4055
OZKGY	2012-2016	1060	0.0003	0.0296	-0.1925	0.2007
OZRDN	2015-2016	306	0.0007	0.0219	-0.1204	0.1125
PAGYO	2013-2016	741	0.0003	0.0117	-0.0447	0.0612
PARSN	1995-2016	5313	0.0013	0.0581	-0.6931	0.6931
PEGYO	1994-2016	5450	0.0007	0.0548	-0.6931	0.6931
PENGD	1998-2016	4510	0.0003	0.0343	-0.2154	0.1972
PETKM	1994-2016	5424	0.0011	0.0463	-0.6931	0.6931
PETUN	2000-2016	3945	0.0011	0.0309	-0.2364	0.2007
PGSUS	2013-2016	759	-0.0002	0.0253	-0.1398	0.0932
PIMAS	1993-2016	5740	0.0009	0.0642	-0.6931	0.6931
PINSU	1993-2016	5618	0.0010	0.0664	-0.6931	0.6931
PKART	2004-2016	2946	0.0001	0.0246	-0.1625	0.1802
PKENT	1992-2016	5964	0.0012	0.0495	-0.2231	0.2763
PLASP	2014-2016	562	-0.0026	0.0473	-0.2231	0.1795
PNSUT	1995-2016	5276	0.0014	0.0410	-0.6931	0.6931
POLHO	2012-2016	992	0.0004	0.0202	-0.1137	0.1447
POLTK	2014-2016	545	0.0016	0.0190	-0.0796	0.1179
PRKAB	1993-2016	5799	0.0010	0.0499	-0.6931	0.6931
PRKME	1997-2016	4626	0.0006	0.0635	-0.6931	0.6931
PRTAS	1996-2013	4415	0.0003	0.0469	-0.2107	0.2364
PRZMA	2012-2016	999	-0.0005	0.0283	-0.2134	0.1487
PSDTC	2014-2016	375	-0.0001	0.0318	-0.1685	0.1082
PTOFS	1993-2015	5393	0.0011	0.0560	-0.6931	0.6931
RAKSE	1993-2005	2925	0.0007	0.0488	-0.2076	0.1872
RANLO	2009-2013	950	-0.0031	0.0332	-0.1655	0.1671

Stock	Time Period	Number of Observations	Mean	S.D.	Min	Max
RAYGS	1997-2016	4693	0.0005	0.0544	-0.4055	0.4055
RHEAG	2000-2016	3970	0.0005	0.0407	-0.2423	0.2113
RKSEV	1994-2005	2576	0.0003	0.0529	-0.1922	0.1896
RODGR	2013-2016	685	-0.0010	0.0385	-0.1715	0.1840
ROYAL	2013-2016	755	-0.0012	0.0170	-0.1083	0.0749
RTALB	2014-2016	486	-0.0003	0.0258	-0.0861	0.1884
RYGYO	2010-2016	1463	-0.0001	0.0228	-0.1214	0.1823
RYSAS	2006-2016	2577	-0.0004	0.0269	-0.1574	0.1519
SAFGY	2007-2016	2310	0.0001	0.0288	-0.1422	0.1691
SAHOL	1997-2016	4708	0.0009	0.0316	-0.1881	0.1911
SAMAT	2011-2016	1223	-0.0008	0.0290	-0.2152	0.1765
SANEL	2013-2016	612	-0.0007	0.0293	-0.2195	0.1662
SANFM	2012-2016	1016	-0.0004	0.0296	-0.1823	0.1809
SANKO	2000-2016	3907	0.0000	0.0252	-0.1978	0.1806
SARKY	1994-2016	5483	0.0011	0.0596	-0.6931	0.6931
SASA	1996-2016	4873	0.0006	0.0330	-0.2729	0.2076
SAYAS	2013-2016	714	0.0008	0.0165	-0.1123	0.1175
SEKFK	2004-2016	2926	-0.0001	0.0314	-0.2377	0.2177
SEKUR	2013-2016	647	0.0000	0.0239	-0.1646	0.0958
SELEC	2006-2016	2524	0.0002	0.0222	-0.1205	0.1149
SELGD	1998-2016	4443	0.0000	0.0402	-0.2097	0.2043
SERVE	1998-2016	4414	0.0001	0.0381	-0.2412	0.2151
SEYKM	2015-2016	192	-0.0015	0.0212	-0.0820	0.0747
SILVR	2006-2016	2483	-0.0001	0.0318	-0.2160	0.1761
SISE	1995-2016	5308	0.0011	0.0675	-0.6931	0.6931
SKBNK	1997-2016	4756	0.0008	0.0436	-0.2877	0.2877
SKPLC	2000-2015	3739	0.0000	0.0417	-0.2305	0.6583
SKTAS	1995-2016	5263	0.0008	0.0441	-0.2513	0.3365
SLVRP	2012-2016	971	-0.0002	0.0162	-0.1308	0.0877
SNGYO	2007-2016	2231	-0.0004	0.0252	-0.1528	0.1252
SNKRN	2015-2016	296	-0.0023	0.0324	-0.1980	0.1823
SNPAM	1994-2016	5331	0.0007	0.0528	-0.4055	0.4055
SODA	2000-2016	4025	0.0007	0.0284	-0.2007	0.1823
SODSN	2012-2016	757	-0.0002	0.0461	-0.2223	0.2261
SONME	1992-2016	5905	0.0009	0.0951	-0.9163	0.9163
SRVGY	2013-2016	756	-0.0001	0.0213	-0.1355	0.1633
TACTR	2013-2016	739	-0.0002	0.0412	-0.2231	0.1823
TARAF	2012-2016	1048	-0.0018	0.0431	-0.2149	0.1934
TATGD	1993-2016	5684	0.0011	0.0408	-0.4055	0.6931
TAVHL	2007-2016	2315	0.0003	0.0256	-0.1762	0.1775
TBORG	1992-2016	5957	0.0011	0.0491	-0.4055	0.6931
TCELL	2000-2016	3965	0.0003	0.0283	-0.1967	0.1769
TCHOL	2006-2016	2250	0.0000	0.0293	-0.1719	0.1719

Stock	Time Period	Number of Observations	Mean	S.D.	Min	Max
TEBNK	2000-2015	3793	0.0008	0.0346	-0.2160	0.2364
TEKTU	2000-2016	3944	0.0000	0.0397	-0.2076	0.2076
TGSAS	2012-2016	982	-0.0003	0.0383	-0.2145	0.1598
THYAO	1994-2016	5519	0.0012	0.0471	-0.6931	0.6931
TIRE	1994-2016	5458	0.0009	0.0491	-0.6931	0.6931
TKFEN	2007-2016	2124	0.0002	0.0246	-0.1754	0.1387
TKNSA	2012-2016	997	-0.0003	0.0209	-0.2116	0.1086
TKURU	2012-2016	875	0.0001	0.0121	-0.0896	0.1323
TMPOL	2013-2016	599	0.0015	0.0352	-0.2226	0.2877
TMSN	2012-2016	859	0.0008	0.0277	-0.2098	0.1843
TNSAS	1996-2006	2450	0.0016	0.0433	-0.2299	0.2231
TOASO	1992-2016	5959	0.0013	0.0468	-0.2384	0.6931
TOPFN	1997-2006	2206	0.0016	0.0524	-0.2364	0.3137
TRCAS	1998-2016	4288	0.0006	0.0340	-0.2109	0.3054
TRGYO	2010-2016	1393	0.0004	0.0223	-0.1726	0.1483
TRKCM	1995-2016	5286	0.0010	0.0415	-0.4055	0.6931
TRNSK	1992-2016	5896	0.0005	0.0587	-0.5596	0.4055
TSGYO	2010-2016	1527	-0.0004	0.0204	-0.1473	0.1466
TSKB	1997-2016	4821	0.0011	0.0691	-0.6931	0.6931
TSKYO	2001-2012	2708	0.0009	0.0390	-0.2231	0.2076
TSPOR	2005-2016	2783	0.0003	0.0304	-0.2167	0.1965
TTKOM	2008-2016	2004	0.0004	0.0186	-0.1101	0.0960
TTRAK	2004-2016	2995	0.0012	0.0244	-0.1530	0.1401
TUCLK	2014-2016	476	0.0008	0.0473	-0.2189	0.1812
TUDDF	1991-2015	5941	0.0011	0.0578	-0.6931	0.6931
TUKAS	1994-2016	5350	0.0005	0.0366	-0.2408	0.2469
TUMTK	2003-2011	1941	-0.0005	0.0453	-0.2207	0.4383
TUPRS	1993-2016	5659	0.0016	0.0513	-0.6931	0.6931
TURGG	2013-2016	697	0.0008	0.0282	-0.1859	0.1869
UKIM	1996-2007	2836	0.0008	0.0407	-0.2513	0.4520
ULAS	2012-2016	940	-0.0001	0.0421	-0.2206	0.1957
ULKER	1996-2016	4871	0.0013	0.0370	-0.2877	0.2877
ULUSE	2014-2016	368	-0.0016	0.0183	-0.1187	0.0735
ULUUN	2014-2016	369	-0.0012	0.0217	-0.1574	0.1065
UMPAS	2015-2016	333	-0.0057	0.0573	-0.2194	0.2076
UNICO	1995-2015	5089	0.0010	0.0544	-0.6931	0.6931
UNTAR	1997-2007	2329	-0.0002	0.0455	-0.4925	0.1951
UNYEC	1996-2016	5057	0.0012	0.0350	-0.2877	0.6931
USAK	1993-2016	5724	0.0008	0.0526	-0.6931	0.6931
USAS	1995-2016	5145	0.0007	0.0380	-0.4055	0.6931
USDTRF	2012-2016	1008	0.0005	0.0064	-0.0364	0.0318
UTPYA	2011-2016	1308	-0.0004	0.0298	-0.1803	0.1638
UYUM	2010-2016	1376	0.0002	0.0217	-0.1522	0.1144

Stock	Time Period	Number of Observations	Mean	S.D.	Min	Max
UZEL	1997-2008	2680	0.0002	0.0383	-0.1967	0.1991
UZERB	2012-2016	922	-0.0028	0.0595	-0.2159	0.2066
VAKBN	2005-2016	2632	0.0002	0.0265	-0.1307	0.1622
VAKFN	1993-2016	5755	0.0009	0.0630	-0.6931	0.6931
VAKKO	1998-2016	4518	0.0004	0.0389	-0.2412	0.2412
VANGD	2011-2016	1180	-0.0005	0.0432	-0.2127	0.1980
VERTU	2015-2016	119	0.0061	0.0333	-0.0588	0.0960
VERUS	2013-2016	621	0.0023	0.0163	-0.0875	0.0978
VESBE	2006-2016	2527	0.0006	0.0287	-0.1937	0.1782
VESTL	1994-2016	5469	0.0012	0.0526	-0.6931	0.6931
VKFYO	1994-2016	5464	0.0008	0.0670	-0.6931	0.6931
VKGYO	1997-2016	4824	0.0010	0.0439	-0.4055	0.4055
VKING	1994-2016	5379	0.0002	0.0397	-0.2551	0.2218
YAPRK	2011-2016	1250	-0.0009	0.0245	-0.1542	0.1674
YATAS	1996-2016	4923	0.0005	0.0373	-0.2311	0.2063
YAYLA	2013-2016	617	-0.0011	0.0340	-0.2638	0.1652
YAZIC	2000-2016	4065	0.0005	0.0275	-0.2513	0.1942
YBTAS	2012-2016	533	-0.0002	0.0533	-0.2141	0.1970
YESIL	2004-2016	2959	-0.0003	0.0332	-0.1614	0.1993
YGGYO	2013-2016	682	0.0010	0.0168	-0.0953	0.1395
YGYO	1999-2016	3922	-0.0003	0.0424	-0.2231	1.0025
YKBNK	1995-2016	5288	0.0011	0.0413	-0.4055	0.6931
YKBYO	1996-2013	4475	0.0013	0.0700	-1.0986	1.0986
YKFIN	1994-2012	4483	0.0014	0.1178	-1.0986	0.6931
YKGYO	1998-2016	4466	0.0002	0.0348	-0.2353	0.2201
YKSGR	1994-2014	4823	0.0013	0.0452	-0.2877	0.2877
YONGA	2015-2016	247	-0.0018	0.0686	-0.2231	0.1906
YTFYO	1999-2009	2436	0.0007	0.0393	-0.2683	0.3102
YUNSA	1992-2016	5958	0.0009	0.0546	-0.6931	0.6931
YYAPI	1995-2016	5243	0.0003	0.0427	-0.2369	0.2326
ZOREN	2000-2016	4001	0.0002	0.0312	-0.2207	0.2177

Table A2. Numbers of all listed stocks per year

Year	Number of Stocks	Year	Number of Stocks
1991	5	2004	304
1992	33	2005	314
1993	72	2006	330
1994	120	2007	335
1995	162	2008	334
1996	188	2009	332
1997	222	2010	353
1998	242	2011	380
1999	250	2012	425
2000	285	2013	444
2001	285	2014	451
2002	289	2015	449
2003	292	2016	437

Table A3. Total number of stocks which are traded in the BIST by years

Year	Total number of traded stocks	Year	Total number of traded stocks
1991	4,730,639	2004	352,909,632
1992	27,951,912	2005	366,040,704
1993	74,849,712	2006	369,225,888
1994	129,700,824	2007	375,726,816
1995	199,052,112	2008	374,247,072
1996	228,741,936	2009	373,598,976
1997	267,841,200	2010	373,937,664
1998	290,606,080	2011	386,470,880
1999	287,019,392	2012	393,592,448
2000	324,333,344	2013	390,860,096
2001	336,545,184	2014	385,279,392
2002	348,163,328	2015	377,822,016
2003	342,964,224	2016	126,739,576

Table A4. Descriptive statistics of 499 stock returns' observations which are traded in the BIST after 2000

Stock	Time Period	Number of Observations	Mean	S.D.	Min.	Max.
ABANA	2000-2008	2080	-0.00067	0.03548	-0.13384	0.15906
ACIBD	2000-2012	3086	0.00131	0.03057	-0.19416	0.18924
ACSEL	2012-2016	959	0.00005	0.03351	-0.20403	0.19570
ADANA	2000-2016	4094	0.00087	0.02662	-0.22314	0.18232
ADBGR	2000-2016	4093	0.00103	0.04054	-0.93827	0.89382
ADEL	2000-2016	4095	0.00110	0.02971	-0.21357	0.19783
ADESE	2011-2016	1130	0.00068	0.02527	-0.19639	0.14437
ADNAC	2000-2016	4095	0.00068	0.04902	-0.40547	0.40547
AEFES	2000-2016	3960	0.00067	0.02713	-0.23639	0.23052
AFMAS	2004-2014	2379	0.00050	0.02972	-0.14458	0.18540
AFYON	2000-2016	4092	0.00091	0.04859	-0.68007	1.78122
AGYO	2002-2016	3570	0.00044	0.02829	-0.16197	0.16990
AKALT	2000-2013	3259	0.00038	0.03136	-0.16127	0.18473
AKBNK	2000-2016	4096	0.00057	0.02947	-0.23639	0.18814
AKCNS	2000-2016	4096	0.00065	0.02756	-0.17327	0.18514
AKENR	2000-2016	3969	0.00004	0.02750	-0.18760	0.18924
AKFEN	2010-2016	1500	0.00022	0.02079	-0.19106	0.18232
AKFGY	2011-2016	1253	-0.00029	0.02154	-0.14256	0.13425
AKGRT	2000-2016	4096	0.00061	0.03256	-0.20764	0.24935
AKGUV	2012-2016	963	-0.00035	0.02728	-0.18639	0.18183
AKIPD	2000-2009	2495	0.00012	0.03909	-0.21292	0.19933
AKMGY	2005-2016	2782	0.00033	0.02399	-0.15379	0.18232
AKPAZ	2013-2016	725	-0.00230	0.02995	-0.20067	0.18232
AKSA	2000-2016	4096	0.00060	0.02741	-0.18721	0.20294
AKSEL	2011-2016	1196	-0.00081	0.04070	-0.21784	0.19753
AKSEN	2010-2016	1498	-0.00038	0.02040	-0.15787	0.10536
AKSGY	2000-2016	4094	0.00040	0.02972	-0.14310	0.18659
AKSUE	2000-2016	4093	0.00051	0.03285	-0.22350	0.22001
ALARK	2000-2016	4096	0.00015	0.02506	-0.19106	0.17096
ALBRK	2007-2016	2225	0.00009	0.01970	-0.11617	0.12569
ALCAR	2000-2016	4096	0.00052	0.02690	-0.19123	0.18721
ALCTL	2000-2016	4096	-0.00006	0.03322	-0.18232	0.20661
ALGYO	2000-2016	4095	0.00061	0.02733	-0.16908	0.20067
ALKA	2000-2016	3886	0.00022	0.03090	-0.26439	0.21357
ALKIM	2000-2016	4054	0.00061	0.02877	-0.23361	0.19416
ALNTF	2000-2015	3887	0.00032	0.03494	-0.20067	0.20764
ALYAG	2000-2016	3992	-0.00040	0.03668	-0.23111	0.20972
ANACM	2000-2016	4096	0.00059	0.02950	-0.22314	0.20764
ANALE	2010-2016	1480	-0.00042	0.02167	-0.14953	0.15739

Stock	Time Period	Number of Observations	Mean	S.D.	Min.	Max.
ANELT	2005-2016	2677	-0.00006	0.02550	-0.22124	0.18325
ANHYT	2000-2016	4059	0.00062	0.03227	-0.20764	0.20764
ANSA	2005-2016	2756	-0.00031	0.03758	-0.22314	0.19337
ANSGR	2000-2016	4096	0.00057	0.03230	-0.22314	0.22314
ARAT	2000-2007	1833	-0.00080	0.04418	-0.23361	0.22314
ARBUL	2014-2016	463	-0.00383	0.04309	-0.22149	0.18430
ARCLK	2000-2016	4096	0.00060	0.02969	-0.20187	0.22314
ARENA	2000-2016	3886	0.00036	0.03236	-0.19237	0.22314
ARFYO	2000-2014	3701	0.00050	0.03851	-0.32158	0.27444
ARMDA	2006-2016	2488	0.00092	0.02958	-0.15415	0.18185
ARSAN	2000-2016	4096	0.00027	0.03705	-0.26826	0.23484
ARTI	2006-2016	2491	-0.00053	0.03951	-0.22712	0.18831
ARTOG	2012-2015	597	-0.00245	0.06457	-0.86020	0.19390
ASCEL	2012-2016	930	-0.00447	0.05133	-0.21673	0.19671
ASELS	2000-2016	4096	0.00098	0.03152	-0.24922	0.20067
ASLAN	2000-2016	4094	0.00101	0.03950	-0.22166	0.21571
ASUZU	2000-2016	4096	0.00048	0.03139	-0.21726	0.18514
ASYAB	2006-2016	2480	-0.00033	0.03091	-0.22516	0.20312
ATAC	2011-2014	744	-0.00346	0.04034	-0.21667	0.16106
ATAGY	2000-2016	4094	0.00047	0.03569	-0.23052	0.26826
ATEKS	2000-2016	4096	0.00069	0.03450	-0.19416	0.20534
ATLAS	2000-2016	4084	0.00037	0.03808	-0.30538	0.19736
ATPET	2012-2016	892	-0.00059	0.03722	-0.22235	0.18527
ATSYH	2000-2016	4091	-0.00001	0.03420	-0.22314	0.18805
AVGYO	2000-2016	4094	0.00017	0.04321	-0.23399	0.21466
AVHOL	2012-2016	856	-0.00042	0.03872	-0.22314	0.17115
AVISA	2014-2016	373	0.00090	0.01622	-0.06049	0.11087
AVOD	2011-2016	1111	-0.00034	0.02723	-0.20448	0.14660
AVTUR	2007-2016	2264	0.00016	0.04154	-0.22149	0.20516
AYCES	2000-2016	4096	0.00057	0.03474	-0.21825	0.20764
AYEN	2000-2016	3970	0.00037	0.02905	-0.25131	0.19783
AYES	2013-2016	797	-0.00190	0.04884	-0.21737	0.19527
AYGAZ	2000-2016	4091	0.00061	0.02558	-0.19611	0.18805
BAGFS	2000-2016	4096	0.00069	0.02973	-0.18232	0.19290
BAKAB	2000-2016	4096	0.00044	0.02892	-0.23639	0.21825
BAKAN	2013-2016	724	-0.00156	0.04603	-0.22491	0.19476
BALAT	2012-2016	926	-0.00605	0.04631	-0.21903	0.20334
BANVT	2000-2016	4096	0.00014	0.03037	-0.21357	0.20391
BASCM	2012-2016	926	-0.00108	0.03341	-0.21637	0.19643
BERDN	2000-2013	3372	-0.00083	0.03879	-0.17656	0.21278
BEYAZ	2012-2016	1029	-0.00022	0.04049	-0.21409	0.18366

Stock	Time Period	Number of Observations	Mean	S.D.	Min.	Max.
BFREN	2000-2016	4090	0.00071	0.05467	-1.93938	1.93118
BIMAS	2005-2016	2718	0.00124	0.02352	-0.16651	0.21720
BISAS	2000-2016	4090	-0.00007	0.04020	-0.26663	0.20972
BIZIM	2011-2016	1322	-0.00035	0.01880	-0.14546	0.07892
BJKAS	2002-2016	3566	0.00049	0.04185	-0.40819	1.21756
BLCYT	2011-2016	1249	-0.00027	0.02744	-0.21131	0.17920
BMEKS	2011-2016	1272	-0.00038	0.01796	-0.09531	0.12332
BMELK	2014-2016	476	-0.00180	0.02929	-0.21278	0.17520
BNKTRF	2009-2016	1678	0.00018	0.02021	-0.11033	0.09971
BNTAS	2015-2016	244	-0.00116	0.02062	-0.08895	0.18232
BOLUC	2000-2016	4096	0.00090	0.02713	-0.20067	0.20067
BOSSA	2000-2016	4096	0.00058	0.03279	-0.25131	0.20479
BOYNR	2000-2016	4049	0.00001	0.03466	-0.25131	0.20114
BOYP	2000-2016	4096	0.00096	0.03339	-0.20679	0.19311
BRISA	2000-2016	4096	0.00080	0.02943	-0.18924	0.19542
BRKO	2009-2016	1764	-0.00027	0.02650	-0.13353	0.19783
BRKSN	2011-2016	1321	0.00020	0.04023	-0.21616	0.19422
BRMEN	2000-2016	4087	0.00003	0.03563	-0.21730	0.22220
BRSAN	2000-2016	4096	0.00081	0.03147	-0.22314	0.23361
BRYAT	2000-2016	4096	0.00088	0.03062	-0.22089	0.19027
BSHEV	2000-2014	3546	0.00102	0.03248	-0.22195	0.22895
BSOKE	2000-2016	4015	0.00040	0.02754	-0.16705	0.17185
BTCIM	2000-2016	4096	0.00047	0.02596	-0.17905	0.19500
BUCIM	2000-2016	4096	0.00041	0.01882	-0.16363	0.17918
BURCE	2000-2016	4096	0.00056	0.03965	-0.24116	0.20067
BURVA	2004-2016	3012	-0.00014	0.03318	-0.19637	0.19459
BYSAN	2000-2008	1944	0.00021	0.05521	-0.29849	0.21357
CBSBO	2000-2013	3494	-0.00034	0.04189	-0.21082	0.20634
CCOLA	2006-2016	2511	0.00064	0.02427	-0.14310	0.16696
CELHA	2000-2016	4096	0.00021	0.03278	-0.24116	0.20816
CEMAS	2010-2016	1468	-0.00058	0.03347	-0.18833	0.19499
CEMTS	2000-2016	4096	0.00065	0.03120	-0.22314	0.22314
CIMSA	2000-2016	4096	0.00085	0.02628	-0.17435	0.21622
CLKHO	2011-2014	805	-0.00185	0.03400	-0.19643	0.15090
CMBTN	2000-2016	4096	0.00052	0.03544	-0.24256	0.19618
CMENT	2000-2016	4094	0.00053	0.02825	-0.18641	0.19706
CMLOJ	2000-2007	1915	0.00108	0.03862	-0.21030	0.17288
COMDO	2000-2016	4095	0.00051	0.03161	-0.21511	0.21415
COSMO	2000-2016	4061	0.00045	0.03620	-0.24116	0.18805
CRDFA	2000-2016	4068	0.00089	0.05722	-0.69315	0.69315
CRFSA	2015-2016	187	-0.00045	0.02731	-0.07730	0.18187

Stock	Time Period	Number of Observations	Mean	S.D.	Min.	Max.
CUSAN	2016-2016	52	0.00955	0.03412	-0.02899	0.18153
CYTAS	2000-2009	2344	0.00096	0.04600	-0.27329	0.21131
DAGHL	2000-2016	4093	0.00049	0.03594	-0.22314	0.21511
DAGI	2011-2016	1239	0.00020	0.02536	-0.19362	0.16950
DARDL	2000-2016	3984	-0.00001	0.04255	-0.24420	0.63406
DENCM	2000-2016	4096	0.00053	0.03099	-0.21380	0.21571
DENGE	2012-2016	941	-0.00020	0.03647	-0.22172	0.19264
DENIZ	2004-2016	2915	0.00055	0.03118	-0.22314	0.20862
DENTA	2000-2014	3463	0.00068	0.03221	-0.22143	0.25131
DERIM	2000-2016	4092	0.00054	0.03618	-0.23995	0.19597
DESA	2004-2016	3019	-0.00022	0.02627	-0.17327	0.14981
DESPC	2010-2016	1363	0.00050	0.02514	-0.17979	0.17480
DEVA	2000-2016	4096	0.00074	0.03495	-0.23052	0.20764
DGATE	2006-2016	2576	0.00077	0.03297	-0.21622	0.17347
DGGYO	2000-2016	4096	0.00072	0.03616	-0.26236	0.20764
DGKLB	2000-2016	4095	0.00003	0.03431	-0.20909	0.21256
DGZTE	2000-2016	4096	0.00019	0.03785	-0.20067	0.20835
DIRIT	2012-2016	922	-0.00305	0.03997	-0.21577	0.19753
DITAS	2000-2016	4096	0.00031	0.03255	-0.19189	0.20067
DJIMTF	2006-2016	2514	0.00015	0.01420	-0.08168	0.09463
DJISTF	2005-2016	2845	0.00050	0.01748	-0.09512	0.12142
DMSAS	2000-2016	4096	0.00046	0.03056	-0.28768	0.26236
DOAS	2004-2016	2990	0.00064	0.02758	-0.17228	0.12828
DOBUR	2000-2016	4041	0.00007	0.03499	-0.20067	0.24715
DOCO	2010-2016	1367	0.00143	0.01662	-0.13724	0.11664
DOGUB	2000-2016	4076	0.00010	0.04170	-0.25131	0.21131
DOHOL	2000-2016	4095	-0.00012	0.03489	-0.22722	0.18805
DURDO	2000-2016	4096	0.00036	0.03581	-0.22032	0.20067
DYHOL	2000-2014	3673	-0.00027	0.03802	-0.22677	0.19302
DYOBY	2000-2016	4095	-0.00019	0.03567	-0.22067	0.20378
DZGYO	2000-2016	4094	0.00064	0.05003	-0.57752	0.40547
ECBYO	2000-2016	4096	0.00058	0.03110	-0.22884	0.21357
ECILC	2000-2016	4096	0.00068	0.03205	-0.20067	0.22314
ECYAP	2000-2015	3832	0.00048	0.02799	-0.24512	0.18572
ECZYT	2000-2016	4096	0.00063	0.02845	-0.20252	0.21741
EDIP	2000-2016	4096	0.00027	0.03331	-0.22314	0.20067
EFES	2000-2006	1742	0.00050	0.03665	-0.17707	0.18805
EGCYH	2000-2016	4089	0.00009	0.04256	-0.22314	0.22314
EGCYO	2000-2016	4086	0.00017	0.03753	-0.21357	0.20224
EGEEN	2000-2016	4095	0.00115	0.03473	-0.21383	0.20360
EGGUB	2000-2016	4096	0.00088	0.03090	-0.17435	0.21030

Stock	Time Period	Number of Observations	Mean	S.D.	Min.	Max.
EGLYO	2000-2016	4095	0.00045	0.03291	-0.22314	0.21357
EGPRO	2000-2016	4087	0.00082	0.03344	-0.20764	0.22314
EGSER	2000-2016	4096	0.00054	0.03439	-0.20360	0.20360
EGYO	2000-2013	3020	-0.00063	0.04223	-0.19290	0.26236
EKGYO	2010-2016	1354	0.00039	0.02197	-0.13469	0.11345
EKIZ	2010-2016	1455	-0.00172	0.03737	-0.21131	0.19736
EMKEL	2000-2016	4092	-0.00022	0.03671	-0.22054	0.19961
EMNIS	2000-2016	4096	0.00011	0.03670	-0.22929	0.21261
EMPAS	2000-2000	33	-0.00114	0.07614	-0.17435	0.13976
EMSAN	2000-2000	33	0.00319	0.08067	-0.13613	0.17934
ENKAI	2000-2016	4096	0.00074	0.02791	-0.19416	0.19416
EPLAS	2000-2016	4054	0.00015	0.04295	-0.22314	0.22314
ERBOS	2000-2016	4096	0.00067	0.03028	-0.20692	0.25022
EREGL	2000-2016	4093	0.00080	0.03207	-0.25131	0.28768
ERICO	2011-2014	791	-0.00278	0.04466	-0.21782	0.21337
ERSU	2000-2016	4034	0.00014	0.03446	-0.23967	0.20067
ESCOM	2000-2016	3959	0.00003	0.03609	-0.32975	0.19933
ESEMS	2000-2016	4084	-0.00039	0.04418	-0.19464	0.20430
ETILR	2012-2016	953	-0.00041	0.04088	-0.22314	0.13931
ETYAT	2008-2016	2003	-0.00042	0.03310	-0.22154	0.19621
EUHOL	2010-2016	1477	-0.00076	0.04245	-0.23512	0.19337
EUKYO	2011-2016	1186	-0.00064	0.03713	-0.21540	0.17609
EUYO	2006-2016	2481	-0.00026	0.03188	-0.20067	0.19753
FBISTF	2007-2016	2144	0.00041	0.00295	-0.02179	0.01707
FENER	2004-2016	3072	0.00053	0.02779	-0.21530	0.20121
FENIS	2000-2016	4091	0.00007	0.03752	-0.20067	0.19717
FFKRL	2000-2016	4089	0.00075	0.03522	-0.20764	0.23639
FINBN	2000-2016	4095	0.00086	0.03694	-0.33647	0.22465
FISCTR	2012-2016	487	-0.00044	0.04069	-0.35550	0.31449
FLAP	2012-2016	965	-0.00156	0.03860	-0.21278	0.16772
FMIZP	2000-2016	4095	0.00098	0.03359	-0.21131	0.21825
FNSYO	2000-2014	3719	0.00028	0.03283	-0.24116	0.20764
FONSY	2006-2016	2381	-0.00050	0.02817	-0.22190	0.19574
FORTS	2000-2011	2781	0.00081	0.03611	-0.22314	0.21357
FRIGO	2000-2016	4085	-0.00027	0.03633	-0.21661	0.19987
FROTO	2000-2016	4096	0.00097	0.02889	-0.17589	0.18840
FVORI	2000-2015	3664	-0.00039	0.04284	-0.23219	0.21357
FYKBNK	2012-2016	355	-0.00068	0.06371	-0.58192	0.49865
GARAN	2000-2016	4096	0.00067	0.03231	-0.21357	0.19671
GARFA	2000-2016	4095	0.00055	0.03862	-0.21372	0.22314
GDKGS	2006-2016	2326	0.00047	0.02613	-0.16551	0.20585

Stock	Time Period	Number of Observations	Mean	S.D.	Min.	Max.
GEDIK	2010-2016	1405	0.00065	0.01519	-0.07090	0.18232
GEDIZ	2000-2016	3999	-0.00036	0.04008	-0.22314	0.18641
GEDZA	2014-2016	575	-0.00029	0.03051	-0.13276	0.17923
GENTS	2000-2016	4095	0.00059	0.02980	-0.22314	0.20067
GENYH	2000-2016	4069	0.00001	0.04515	-0.22314	0.21357
GEREL	2003-2016	3261	0.00016	0.02870	-0.23823	0.19783
GIMA	2000-2006	1655	-0.00022	0.03329	-0.20006	0.20360
GLBMD	2011-2016	1212	-0.00104	0.02831	-0.20294	0.18514
GLDTRF	2006-2016	2414	0.00055	0.01252	-0.09257	0.08920
GLRYH	2006-2016	2501	-0.00018	0.02948	-0.21082	0.18232
GLYHO	2000-2016	4092	0.00009	0.03597	-0.25489	0.19611
GMSTR	2012-2016	1007	-0.00010	0.01589	-0.12203	0.09696
GNPWR	2005-2016	2704	-0.00045	0.04032	-0.19611	0.20909
GOLDPF	2010-2016	1447	0.00048	0.01100	-0.10134	0.05510
GOLDS	2000-2013	3320	-0.00040	0.03404	-0.21425	0.20526
GOLTS	2000-2016	3985	0.00076	0.03150	-0.18954	0.42886
GOODY	2000-2016	4096	0.00067	0.02948	-0.17610	0.18803
GOZDE	2010-2016	1580	0.00104	0.03009	-0.19085	0.19611
GRNYO	2000-2016	4095	0.00085	0.05645	-0.69315	0.69315
GRUND	2000-2009	2380	-0.00030	0.03406	-0.20224	0.19671
GSDDE	2000-2016	4096	0.00037	0.03868	-0.25783	0.23639
GSDHO	2000-2016	4096	0.00006	0.03834	-0.22957	0.21256
GSRAY	2002-2016	3566	0.00030	0.02948	-0.22131	0.17654
GUBRF	2000-2016	4096	0.00090	0.04258	-0.28768	0.28768
GUSGR	2000-2016	4096	0.00039	0.03238	-0.25951	0.19416
GYHOL	2000-2016	3943	0.00050	0.03191	-0.21319	0.20764
HALKB	2007-2016	2254	0.00017	0.02732	-0.13173	0.18693
HALKS	2012-2016	983	0.00144	0.05253	-0.57639	0.44940
HATEK	2011-2016	1335	-0.00021	0.03404	-0.21409	0.19579
HDFGS	2015-2016	316	0.00022	0.05549	-0.22194	0.18232
HEKTS	2000-2016	4096	0.00071	0.03175	-0.20067	0.20067
HITIT	2012-2015	753	-0.00019	0.03564	-0.20901	0.16445
HLGYO	2013-2016	802	-0.00017	0.01610	-0.13103	0.08618
HURGZ	2000-2016	4096	-0.00004	0.03435	-0.24784	0.20203
HZNDR	2000-2016	4052	0.00068	0.03520	-0.22314	0.19845
ICBCT	2000-2016	4096	0.00041	0.03558	-0.21905	0.22164
IDAS	2000-2016	4091	-0.00053	0.03803	-0.22314	0.19828
IDGYO	2010-2016	1469	-0.00002	0.03852	-0.20972	0.19416
IEYHO	2000-2016	4096	-0.00057	0.04156	-0.21250	0.33526
IHEVA	2000-2016	3854	-0.00011	0.04161	-0.24116	0.89382
IHGZT	2010-2016	1482	-0.00078	0.03300	-0.19106	0.18118

Stock	Time Period	Number of Observations	Mean	S.D.	Min.	Max.
IHLAS	2000-2016	3860	-0.00078	0.03822	-0.23052	0.71335
IHMAD	2000-2016	4083	0.00013	0.04506	-0.31943	0.22024
IHYAY	2010-2016	1382	-0.00146	0.03137	-0.16315	0.19490
INDES	2004-2016	2985	0.00066	0.02220	-0.14930	0.15600
INFO	2011-2016	1148	-0.00048	0.02840	-0.21117	0.15996
INTEM	2000-2016	4096	0.00048	0.03199	-0.20430	0.21131
IPEKE	2000-2016	3973	0.00028	0.04193	-0.25783	0.20067
IS30F	2009-2016	1780	0.00066	0.01597	-0.09312	0.06426
ISATR	2000-2016	757	0.00021	0.06819	-0.38350	0.25442
ISBIR	2012-2016	850	-0.00291	0.04029	-0.21440	0.19436
ISBTR	2000-2016	3789	-0.00008	0.02965	-0.18659	0.21801
ISCTR	2000-2016	4096	0.00033	0.03001	-0.20909	0.20383
ISDMR	2016-2016	25	0.00826	0.10741	-0.22234	0.18232
ISFIN	2000-2016	4041	0.00067	0.04347	-0.40547	0.40547
ISGSY	2004-2016	2900	0.00030	0.01960	-0.11478	0.17997
ISGYO	2000-2016	4096	0.00032	0.02924	-0.21511	0.18721
ISKUR	2001-2016	1276	0.00178	0.08308	-0.57561	0.56798
ISMEN	2007-2016	2255	0.00021	0.02064	-0.11551	0.13613
IST30F	2009-2016	1780	0.00066	0.01597	-0.09312	0.06426
ISY30F	2007-2016	2250	0.00035	0.01756	-0.08649	0.11994
ISYAT	2000-2016	4096	0.00074	0.04244	-0.28768	0.28768
ISYHO	2000-2014	3689	-0.00080	0.03863	-0.23257	0.22314
ITTFH	2010-2016	1596	-0.00077	0.02530	-0.21281	0.15415
IZFAS	2014-2016	460	-0.00077	0.03520	-0.12848	0.18678
IZMDC	2000-2016	4096	0.00055	0.03395	-0.22314	0.18232
IZOCM	2000-2016	4096	0.00094	0.03124	-0.18232	0.19863
IZTAR	2013-2016	625	-0.00061	0.04049	-0.21575	0.32583
JANTS	2012-2016	925	0.00067	0.02840	-0.17970	0.11617
KAPLM	2000-2016	4093	0.00035	0.03832	-0.23361	0.21357
KAREL	2006-2016	2398	0.00012	0.02260	-0.12136	0.17825
KARSN	2000-2016	4062	-0.00016	0.03217	-0.21622	0.20955
KARTN	2000-2016	4088	0.00075	0.02871	-0.16578	0.20796
KATMR	2010-2016	1377	0.00058	0.03155	-0.21371	0.18435
KAVPA	2000-2008	2143	-0.00028	0.03436	-0.18507	0.19877
KCHOL	2000-2016	4088	0.00053	0.02793	-0.20067	0.18232
KENT	2000-2016	4096	0.00089	0.03590	-0.21949	0.19511
KERVN	2000-2016	4091	-0.00019	0.04310	-0.23180	0.18499
KERVT	2000-2016	4074	0.00049	0.04220	-0.22778	0.59029
KILER	2011-2015	1241	-0.00043	0.02605	-0.16139	0.19591
KIPA	2000-2016	4096	0.00041	0.02798	-0.22314	0.23639
KLGYO	2011-2016	1268	-0.00073	0.02547	-0.15040	0.18232

Stock	Time Period	Number of Observations	Mean	S.D.	Min.	Max.
KLMSN	2000-2016	4096	0.00039	0.03131	-0.22112	0.20972
KLNMA	2000-2016	4094	-0.00014	0.03234	-0.23077	0.21472
KNFRT	2000-2016	4096	0.00066	0.03599	-0.17447	0.19208
KOHML	2012-2016	866	-0.00087	0.02948	-0.21272	0.18854
KONYA	2000-2016	4096	0.00102	0.02933	-0.18180	0.18818
KORDS	2000-2016	4095	0.00034	0.02684	-0.22314	0.21217
KOTKS	2000-2006	1714	-0.00079	0.04138	-0.21511	0.19004
KOZAA	2003-2016	3318	0.00044	0.03653	-0.19783	0.20479
KOZAL	2010-2016	1566	0.00022	0.02953	-0.21396	0.14384
KPHOL	2005-2016	2628	-0.00045	0.03687	-0.22314	0.18232
KRATL	2012-2016	940	-0.00090	0.02344	-0.22314	0.18572
KRDMA	2000-2016	4096	0.00073	0.05060	-0.40547	0.40547
KRDMB	2000-2016	4096	0.00078	0.05969	-0.69315	0.69315
KRDMD	2000-2016	4096	0.00067	0.05983	-0.69315	0.69315
KRGYO	2014-2016	503	-0.00018	0.02726	-0.12818	0.17888
KRONT	2011-2016	1242	0.00020	0.03202	-0.17798	0.19987
KRSAN	2012-2016	947	-0.00180	0.04005	-0.19661	0.17721
KRSTL	2000-2016	4068	-0.00005	0.03698	-0.34831	0.22567
KRTEK	2000-2016	4093	0.00016	0.03254	-0.21460	0.22314
KSTUR	2014-2016	436	-0.00461	0.07629	-0.21545	0.19498
KUTPO	2000-2016	4094	0.00067	0.03322	-0.62706	0.22730
KUYAS	2012-2016	911	0.00004	0.04112	-0.21677	0.19807
LATEK	2010-2015	1264	-0.00226	0.03698	-0.16551	0.24512
LIDFA	2014-2016	472	0.00011	0.02347	-0.06899	0.17407
LINK	2000-2016	3890	0.00003	0.03916	-0.23497	0.20986
LIOYS	2000-2006	1595	-0.00065	0.03584	-0.22314	0.20585
LKMNH	2011-2016	1324	0.00017	0.02656	-0.16882	0.17848
LOGO	2000-2016	4012	0.00097	0.03308	-0.20764	0.20252
LUKSK	2000-2016	4095	0.00048	0.03752	-0.23841	0.22314
MAALT	2000-2016	4096	0.00043	0.03504	-0.21357	0.19913
MAKTK	2000-2016	4087	0.00003	0.04396	-0.22314	0.24686
MANGO	2010-2015	1234	-0.00202	0.04490	-0.25593	0.22314
MARTI	2000-2016	4096	0.00009	0.03517	-0.24512	0.23361
MCTAS	2012-2016	984	0.00027	0.02127	-0.12311	0.18232
MEGAP	2012-2016	994	-0.00119	0.03688	-0.20018	0.17351
MEGES	2000-2008	2217	-0.00008	0.04763	-0.36291	0.19671
MEMSA	2000-2016	4081	-0.00033	0.04459	-0.25131	0.22957
MENBA	2013-2016	715	-0.00040	0.02798	-0.18577	0.17905
MEPET	2011-2016	1201	-0.00050	0.04369	-0.21527	0.19711
MERIT	2012-2016	882	-0.00007	0.06136	-0.22314	0.19648
MERKO	2000-2016	4095	0.00001	0.03451	-0.23180	0.20972

Stock	Time Period	Number of Observations	Mean	S.D.	Min.	Max.
METAL	2006-2016	2483	-0.00015	0.03830	-0.20067	0.19913
METRO	2000-2016	4093	-0.00007	0.03548	-0.23733	0.22314
METUR	2002-2016	3461	-0.00005	0.03488	-0.22030	0.20164
MGROS	2000-2016	4094	0.00044	0.02718	-0.20494	0.19966
MIPAZ	2000-2016	4096	-0.00033	0.03704	-0.22581	0.18659
MMCAS	2011-2016	1107	-0.00094	0.05622	-0.22442	0.19382
MNDRS	2000-2016	3955	0.00006	0.03649	-0.25378	0.22884
MRDIN	2000-2016	4096	0.00095	0.02589	-0.15415	0.25131
MRGYO	2010-2016	1411	-0.00084	0.02700	-0.20252	0.20294
MRHSL	2000-2016	4096	0.00047	0.03142	-0.21233	0.20224
MRTGG	2005-2016	2584	-0.00056	0.04398	-0.22099	0.19358
MUTLU	2000-2015	3802	0.00093	0.03429	-0.54411	0.21357
MZHLD	2000-2016	4052	0.00010	0.04056	-0.21622	0.22739
NETAS	2000-2016	4095	0.00020	0.03272	-0.21328	0.18972
NIBAS	2012-2016	1047	-0.00127	0.03184	-0.19497	0.18232
NTHOL	2000-2016	4095	0.00038	0.03429	-0.30538	0.22314
NTTUR	2000-2016	4096	0.00029	0.03513	-0.20764	0.23361
NUGYO	2000-2016	4097	0.00052	0.03527	-0.21800	0.21131
NUHCM	2000-2016	4036	0.00052	0.02223	-0.15101	0.19189
ODAS	2013-2016	743	0.00041	0.02709	-0.13624	0.16455
OLMIP	2000-2016	4097	0.00064	0.02912	-0.22266	0.20824
ORGE	2012-2016	999	0.00081	0.04226	-0.22083	0.18531
ORMA	2013-2016	628	-0.00479	0.06568	-0.21636	0.19586
OSMEN	2012-2016	744	0.00044	0.05675	-0.22314	0.19722
OSTIM	2012-2016	993	0.00025	0.05770	-0.57674	0.44947
OTKAR	2000-2016	4097	0.00092	0.02999	-0.22801	0.19455
OYAYO	2007-2016	2266	-0.00010	0.02798	-0.14732	0.18232
OYLUM	2012-2016	1006	-0.00008	0.03512	-0.19725	0.20935
OYSAC	2000-2007	1962	0.00125	0.03106	-0.21357	0.18572
OZBAL	2011-2016	1199	-0.00080	0.03296	-0.20067	0.19949
OZGYO	2000-2016	4096	0.00049	0.03607	-0.20340	0.21357
OZKGY	2012-2016	1060	0.00034	0.02958	-0.19254	0.20067
OZRDN	2015-2016	306	0.00073	0.02192	-0.12040	0.11248
PAGYO	2013-2016	741	0.00029	0.01168	-0.04474	0.06121
PARSN	2000-2016	4096	0.00096	0.03500	-0.21256	0.20764
PEGYO	2000-2016	4094	0.00015	0.03901	-0.22124	0.21256
PENGD	2000-2016	4097	0.00003	0.03256	-0.21536	0.19717
PETKM	2000-2016	4087	0.00022	0.02896	-0.22801	0.20067
PETUN	2000-2016	3945	0.00107	0.03091	-0.23639	0.20067
PGSUS	2013-2016	759	-0.00024	0.02529	-0.13976	0.09320
PIMAS	2000-2016	4097	0.00004	0.03292	-0.20875	0.22884

Stock	Time Period	Number of Observations	Mean	S.D.	Min.	Max.
PINSU	2000-2016	4097	0.00048	0.03182	-0.21511	0.21511
PKART	2004-2016	2946	0.00013	0.02457	-0.16252	0.18022
PKENT	2000-2016	4080	0.00068	0.04067	-0.21622	0.19337
PLASP	2014-2016	562	-0.00263	0.04732	-0.22314	0.17947
PNSUT	2000-2016	4097	0.00090	0.02993	-0.19237	0.19106
POLHO	2012-2016	992	0.00038	0.02023	-0.11366	0.14474
POLTK	2014-2016	545	0.00164	0.01901	-0.07959	0.11792
PRKAB	2000-2016	4097	0.00036	0.02987	-0.25951	0.18659
PRKME	2000-2016	4096	0.00108	0.03982	-0.27029	0.28768
PRTAS	2000-2013	3502	-0.00046	0.04336	-0.21072	0.21791
PRZMA	2012-2016	999	-0.00047	0.02833	-0.21337	0.14875
PSDTC	2014-2016	375	-0.00005	0.03181	-0.16846	0.10821
PTOFS	2000-2015	3822	0.00016	0.02936	-0.20714	0.22751
RAKSE	2000-2005	1340	-0.00076	0.04626	-0.16705	0.13005
RANLO	2009-2013	950	-0.00307	0.03319	-0.16551	0.16705
RAYGS	2000-2016	4096	0.00035	0.03719	-0.22314	0.20764
RHEAG	2000-2016	3970	0.00052	0.04067	-0.24231	0.21131
RKSEV	2000-2005	1335	0.00046	0.05335	-0.19216	0.17435
RODGR	2013-2016	685	-0.00095	0.03849	-0.17149	0.18400
ROYAL	2013-2016	755	-0.00122	0.01697	-0.10834	0.07490
RTALB	2014-2016	486	-0.00031	0.02576	-0.08613	0.18836
RYGYO	2010-2016	1463	-0.00006	0.02285	-0.12136	0.18232
RYSAS	2006-2016	2577	-0.00040	0.02691	-0.15739	0.15192
SAFGY	2007-2016	2310	0.00011	0.02879	-0.14217	0.16908
SAHOL	2000-2016	4097	0.00040	0.02787	-0.18443	0.18392
SAMAT	2011-2016	1223	-0.00081	0.02897	-0.21523	0.17646
SANEL	2013-2016	612	-0.00069	0.02930	-0.21950	0.16618
SANFM	2012-2016	1016	-0.00037	0.02961	-0.18232	0.18094
SANKO	2000-2016	3907	0.00003	0.02523	-0.19783	0.18058
SARKY	2000-2016	4097	0.00068	0.02702	-0.16705	0.20764
SASA	2000-2016	4097	0.00023	0.02957	-0.27287	0.20271
SAYAS	2013-2016	714	0.00082	0.01655	-0.11233	0.11752
SEKFK	2004-2016	2926	-0.00015	0.03135	-0.23767	0.21772
SEKUR	2013-2016	647	-0.00005	0.02393	-0.16462	0.09585
SELEC	2006-2016	2524	0.00016	0.02224	-0.12049	0.11488
SELGD	2000-2016	4079	-0.00040	0.03813	-0.19885	0.20430
SERVE	2000-2016	4085	0.00007	0.03592	-0.20972	0.21511
SEYKM	2015-2016	192	-0.00148	0.02117	-0.08201	0.07472
SILVR	2006-2016	2483	-0.00013	0.03183	-0.21603	0.17609
SISE	2000-2016	4097	0.00056	0.03041	-0.27193	0.22314
SKBNK	2000-2016	4090	0.00045	0.03802	-0.22494	0.27625

Stock	Time Period	Number of Observations	Mean	S.D.	Min.	Max.
SKPLC	2000-2015	3739	0.00002	0.04167	-0.23052	0.65830
SKTAS	2000-2016	4095	0.00062	0.03553	-0.22314	0.20278
SLVRP	2012-2016	971	-0.00020	0.01624	-0.13077	0.08771
SNGYO	2007-2016	2231	-0.00035	0.02517	-0.15284	0.12516
SNKRN	2015-2016	296	-0.00231	0.03238	-0.19805	0.18232
SNPAM	2000-2016	4094	0.00040	0.03998	-0.26881	0.26570
SODA	2000-2016	4025	0.00071	0.02838	-0.20067	0.18232
SODSN	2012-2016	757	-0.00020	0.04610	-0.22233	0.22610
SONME	2000-2016	4094	0.00045	0.03978	-0.31237	0.30010
SRVGY	2013-2016	756	-0.00012	0.02130	-0.13555	0.16333
TACTR	2013-2016	739	-0.00019	0.04120	-0.22314	0.18232
TARAF	2012-2016	1048	-0.00175	0.04308	-0.21489	0.19337
TATGD	2000-2016	4097	0.00038	0.02743	-0.20067	0.19189
TAVHL	2007-2016	2315	0.00035	0.02556	-0.17619	0.17755
TBORG	2000-2016	4097	0.00053	0.03202	-0.21441	0.22166
TCELL	2000-2016	3965	0.00026	0.02832	-0.19671	0.17693
TCHOL	2006-2016	2250	0.00002	0.02931	-0.17185	0.17185
TEBNK	2000-2015	3793	0.00085	0.03456	-0.21595	0.23639
TEKTU	2000-2016	3944	0.00002	0.03973	-0.20764	0.20764
TGSAS	2012-2016	982	-0.00031	0.03828	-0.21450	0.15985
THYAO	2000-2016	4082	0.00034	0.03052	-0.20764	0.17693
TIRE	2000-2016	4096	0.00032	0.03002	-0.19106	0.18924
TKFEN	2007-2016	2124	0.00017	0.02464	-0.17545	0.13871
TKNSA	2012-2016	997	-0.00026	0.02094	-0.21159	0.10857
TKURU	2012-2016	875	0.00006	0.01208	-0.08961	0.13233
TMPOL	2013-2016	599	0.00153	0.03516	-0.22263	0.28768
TMSN	2012-2016	859	0.00083	0.02765	-0.20977	0.18430
TNSAS	2000-2006	1642	-0.00049	0.03768	-0.22992	0.20252
TOASO	2000-2016	4097	0.00091	0.03161	-0.23841	0.21772
TOPFN	2000-2006	1678	0.00160	0.05165	-0.23639	0.31366
TRCAS	2000-2016	4097	0.00017	0.03291	-0.21095	0.24686
TRGYO	2010-2016	1393	0.00038	0.02231	-0.17265	0.14832
TRKCM	2000-2016	4097	0.00057	0.02802	-0.26236	0.22314
TRNSK	2000-2016	4084	-0.00026	0.04942	-0.22314	0.22314
TSGYO	2010-2016	1527	-0.00038	0.02038	-0.14732	0.14660
TSKB	2000-2016	4097	0.00090	0.06064	-0.69315	0.69315
TSKYO	2001-2012	2708	0.00092	0.03901	-0.22314	0.20764
TSPOR	2005-2016	2783	0.00027	0.03040	-0.21671	0.19650
TTKOM	2008-2016	2004	0.00041	0.01861	-0.11011	0.09601
TTRAK	2004-2016	2995	0.00117	0.02439	-0.15304	0.14006
TUCLK	2014-2016	476	0.00078	0.04734	-0.21889	0.18116

Stock	Time Period	Number of Observations	Mean	S.D.	Min.	Max.
TUDDF	2000-2015	3911	0.00025	0.03389	-0.26826	0.19671
TUKAS	2000-2016	4097	0.00013	0.03088	-0.24079	0.19949
TUMTK	2003-2011	1941	-0.00050	0.04530	-0.22067	0.43825
TUPRS	2000-2016	4081	0.00066	0.02723	-0.18540	0.19561
TURGG	2013-2016	697	0.00076	0.02819	-0.18587	0.18690
UKIM	2000-2007	1873	-0.00023	0.03803	-0.19913	0.20709
ULAS	2012-2016	940	-0.00006	0.04212	-0.22063	0.19574
ULKER	2000-2016	4093	0.00103	0.02935	-0.18924	0.22314
ULUSE	2014-2016	368	-0.00157	0.01826	-0.11874	0.07354
ULUUN	2014-2016	369	-0.00121	0.02168	-0.15739	0.10648
UMPAS	2015-2016	333	-0.00567	0.05734	-0.21936	0.20764
UNICO	2000-2015	3970	0.00093	0.03620	-0.20067	0.21869
UNTAR	2000-2007	1758	-0.00113	0.04319	-0.49248	0.19506
UNYEC	2000-2016	4097	0.00069	0.02517	-0.17185	0.19106
USAK	2000-2016	4093	0.00014	0.03634	-0.21759	0.21030
USAS	2000-2016	4097	0.00026	0.03279	-0.24116	0.20764
USDTRF	2012-2016	1008	0.00048	0.00644	-0.03637	0.03178
UTPYA	2011-2016	1308	-0.00040	0.02976	-0.18032	0.16379
UYUM	2010-2016	1376	0.00024	0.02167	-0.15224	0.11441
UZEL	2000-2008	2091	-0.00032	0.03593	-0.18859	0.19913
UZERB	2012-2016	922	-0.00279	0.05945	-0.21589	0.20661
VAKBN	2005-2016	2632	0.00022	0.02650	-0.13070	0.16223
VAKFN	2000-2016	4097	0.00042	0.03732	-0.21109	0.22314
VAKKO	2000-2016	4097	0.00038	0.03571	-0.24116	0.20764
VANGD	2011-2016	1180	-0.00045	0.04315	-0.21271	0.19801
VERTU	2015-2016	119	0.00611	0.03326	-0.05884	0.09601
VERUS	2013-2016	621	0.00228	0.01627	-0.08746	0.09785
VESBE	2006-2016	2527	0.00065	0.02875	-0.19365	0.17817
VESTL	2000-2016	4097	0.00015	0.03100	-0.21837	0.22314
VKFYO	2000-2016	4097	0.00036	0.03760	-0.24116	0.22314
VKGYO	2000-2016	4096	0.00053	0.03516	-0.22258	0.20764
VKING	2000-2016	4096	-0.00023	0.03657	-0.25508	0.22184
YAPRK	2011-2016	1250	-0.00093	0.02452	-0.15415	0.16738
YATAS	2000-2016	4097	0.00022	0.03497	-0.23111	0.20634
YAYLA	2013-2016	617	-0.00111	0.03397	-0.26377	0.16516
YAZIC	2000-2016	4065	0.00051	0.02751	-0.25131	0.19416
YBTAS	2012-2016	533	-0.00023	0.05325	-0.21405	0.19703
YESIL	2004-2016	2959	-0.00031	0.03320	-0.16139	0.19927
YGGYO	2013-2016	682	0.00102	0.01676	-0.09531	0.13946
YGYO	2000-2016	3912	-0.00038	0.04214	-0.22314	1.00247
YKBNK	2000-2016	4089	0.00019	0.03318	-0.23889	0.19052

Stock	Time Period	Number of Observations	Mean	S.D.	Min.	Max.
YKBYO	2000-2013	3499	0.00095	0.03430	-0.28768	0.37086
YKFIN	2000-2012	3135	0.00079	0.03909	-0.16093	0.25593
YKGYO	2000-2016	4092	0.00003	0.03319	-0.23531	0.22006
YKSGR	2000-2014	3566	0.00088	0.03680	-0.25535	0.21706
YONGA	2015-2016	247	-0.00180	0.06855	-0.22314	0.19061
YTFYO	2000-2009	2378	0.00053	0.03914	-0.26826	0.31015
YUNSA	2000-2016	4097	0.00045	0.02845	-0.20764	0.21030
YYAPI	2000-2016	4094	-0.00048	0.03800	-0.23693	0.23262
ZOREN	2000-2016	4001	0.00018	0.03117	-0.22073	0.21772

Table A5. Descriptive Statistics of betas per month

Month	Observation	Mean	S.D.	Min	Max.
2001m1	282	0.9990	0.1798	0.2869	2.1012
2001m2	278	1.0010	0.0689	0.7452	1.3525
2001m3	275	0.9998	0.0896	0.6856	1.2851
2001m4	277	0.9995	0.2260	0.0109	2.5259
2001m5	278	1.0010	0.1499	0.5039	1.5974
2001m6	278	0.9987	0.1715	0.2790	1.5710
2001m7	277	1.0013	0.1698	0.3016	1.7314
2001m8	277	1.0039	0.2950	0.0935	1.7469
2001m9	277	1.0021	0.2368	-0.0588	1.5328
2001m10	278	1.0014	0.3374	-0.0354	3.2484
2001m11	279	1.0071	0.4276	-0.1420	4.5006
2001m12	275	0.9989	0.2002	0.0467	2.1088
2002m1	278	0.9894	0.2054	0.2470	1.6344
2002m2	281	1.0022	0.1958	-0.1201	1.8312
2002m3	284	1.0013	0.2171	0.3568	1.8365
2002m4	285	0.9995	0.3545	0.1897	3.3023
2002m5	285	0.9981	0.2722	0.2675	3.0022
2002m6	284	1.0006	0.2555	-0.1280	2.4298
2002m7	284	0.9995	0.3234	-0.3115	3.0010
2002m8	284	1.0010	0.1511	0.3243	1.4388

Month	Observation	Mean	S.D.	Min	Max.
2002m9	286	1.0017	0.4520	-0.4306	3.1937
2002m10	286	1.0005	0.4598	-0.6787	3.9809
2002m11	286	1.0014	0.2483	0.3393	1.9543
2002m12	286	1.0001	0.1680	0.2727	1.5118
2003m1	286	1.0020	0.3972	-0.1486	2.4044
2003m2	271	1.0060	0.3755	-0.4235	2.8647
2003m3	287	1.0007	0.1483	0.5450	1.4988
2003m4	286	1.0018	0.2955	0.1082	1.9499
2003m5	286	1.0019	0.3607	-0.2984	4.0561
2003m6	287	1.0034	0.4252	-0.3887	3.2871
2003m7	290	0.9985	0.2695	0.0557	2.8308
2003m8	290	0.9997	0.3240	-0.6841	1.9723
2003m9	291	0.9979	0.2998	-0.3301	2.1966
2003m10	290	0.9974	0.2924	0.1160	1.9340
2003m11	283	1.0010	0.3253	0.1208	1.8843
2003m12	290	1.0007	0.4539	-0.6861	2.0817
2004m1	290	0.9993	0.3669	0.1191	3.0921
2004m2	288	0.9979	0.4917	-0.3901	3.9778
2004m3	292	0.9937	0.6473	-0.8253	3.4769
2004m4	292	1.0014	0.2911	-0.1317	2.2812
2004m5	292	1.0014	0.2427	0.4485	3.7791
2004m6	294	1.0020	0.3247	-0.0840	2.5326
2004m7	297	0.9957	0.4023	-0.6932	3.0128
2004m8	298	0.9976	0.5111	-1.7893	3.0418
2004m9	299	0.9991	0.2363	-0.6275	1.5132
2004m10	301	1.0006	0.7262	-0.3184	11.8973
2004m11	302	0.9998	0.3433	-0.4635	2.4732
2004m12	302	0.9972	0.2962	0.0412	2.1595
2005m1	302	1.0029	0.3639	-0.4925	2.2269
2005m2	303	0.9978	0.3389	-0.1253	2.2004
2005m3	303	0.9999	0.2019	0.2093	1.7378
2005m4	302	1.0030	0.2639	0.1201	2.1632

Month	Observation	Mean	S.D.	Min	Max.
2005m5	304	1.0036	0.2719	-0.3566	1.8699
2005m6	304	1.0014	0.3452	-0.0709	2.1949
2005m7	303	1.0005	0.4201	-0.0761	2.6467
2005m8	305	0.9993	0.4065	-0.4563	2.5389
2005m9	305	1.0015	0.4189	-0.6884	2.5300
2005m10	307	1.0030	0.3716	-0.0196	2.7290
2005m11	306	1.0025	0.6280	-0.9597	3.7009
2005m12	309	0.9995	0.7711	-2.2561	4.5138
2006m1	309	1.0024	0.4889	-0.9440	3.4264
2006m2	308	1.0006	0.6253	-0.7008	6.9666
2006m3	314	0.9994	0.3469	-0.3520	2.2796
2006m4	314	1.0004	0.5365	-0.6435	2.4373
2006m5	314	1.0035	0.2446	0.2729	1.6015
2006m6	320	1.0006	0.1703	0.4646	1.4496
2006m7	323	1.0014	0.2068	-0.0326	1.5744
2006m8	319	1.0058	0.2586	-0.2128	1.8018
2006m9	321	1.0000	0.2526	0.0827	1.8630
2006m10	321	1.0046	0.3034	-0.0705	1.7443
2006m11	322	0.9985	0.2749	0.1575	1.9038
2006m12	322	1.0034	0.3829	-0.0543	2.4327
2007m1	322	0.9929	0.3626	-0.5459	2.0861
2007m2	321	1.0025	0.3574	-0.5136	2.6765
2007m3	323	0.9980	0.4397	-1.8773	2.0587
2007m4	323	0.9996	0.2755	0.2388	1.8421
2007m5	325	0.9967	0.4155	-0.4145	2.4286
2007m6	326	1.0005	0.4486	-2.1155	2.4702
2007m7	327	1.0014	0.3368	-0.0589	1.9520
2007m8	328	1.0013	0.3088	-0.0346	2.1490
2007m9	327	1.0027	0.4345	-0.9771	3.3095
2007m10	325	0.9960	0.3366	-0.3431	2.1542
2007m11	325	1.0014	0.3669	-0.0535	2.2117
2007m12	327	1.0064	0.3889	-0.5816	2.2838

Month	Observation	Mean	S.D.	Min	Max.
2008m1	327	1.0017	0.3737	-0.1492	2.5067
2008m2	328	1.0007	0.3808	-0.2310	2.1357
2008m3	328	1.0001	0.2903	-0.0548	1.6736
2008m4	328	1.0021	0.4878	-0.6521	3.2255
2008m5	326	1.0032	0.4055	-0.5643	2.1607
2008m6	328	1.0026	0.2904	0.0840	2.5607
2008m7	328	0.9982	0.3318	-0.2604	2.0586
2008m8	327	1.0005	0.5562	-1.0685	3.6329
2008m9	327	0.9999	0.2746	-0.0483	1.6766
2008m10	327	1.0001	0.2360	-0.0606	1.7554
2008m11	324	1.0027	0.3009	-0.2361	1.9488
2008m12	324	1.0017	0.3776	-0.4066	1.9252
2009m1	324	0.9994	0.2847	0.0540	1.8958
2009m2	324	1.0020	0.3844	-0.4234	2.5097
2009m3	324	0.9997	0.3714	-0.5165	2.3539
2009m4	324	0.9967	0.3787	-0.7504	2.1543
2009m5	326	1.0040	0.4673	-0.7305	2.5952
2009m6	327	0.9998	0.4437	-1.5070	2.5592
2009m7	325	1.0003	0.3743	-0.3023	2.7561
2009m8	325	0.9975	0.3181	-0.1119	2.6255
2009m9	326	1.0025	0.3834	-0.3504	2.2213
2009m10	326	0.9987	0.2382	-0.2825	1.9488
2009m11	326	1.0009	0.4828	-1.6679	2.6962
2009m12	327	1.0005	0.2698	0.2152	2.0903
2010m1	327	1.0006	0.3365	-0.4644	2.9615
2010m2	329	1.0055	0.3332	-0.4854	1.9889
2010m3	330	1.0019	0.3878	-0.5779	2.4389
2010m4	330	1.0024	0.4401	-1.8434	3.0036
2010m5	331	1.0007	0.2172	0.1055	1.6974
2010m6	334	0.9957	0.3681	-0.7685	2.4206
2010m7	340	1.0033	0.3741	-0.7697	2.3573
2010m8	343	1.0001	0.4268	-0.8749	2.5653

Month	Observation	Mean	S.D.	Min	Max.
2010m9	344	1.0023	0.7008	-1.8457	4.8385
2010m10	344	1.0043	0.5806	-0.8363	4.6874
2010m11	345	0.9981	0.3525	-1.2132	2.2858
2010m12	351	0.9993	0.3973	-0.9271	2.5680
2011m1	351	1.0024	0.2816	-0.6876	1.9476
2011m2	354	1.0027	0.3494	0.1141	2.3439
2011m3	356	0.9998	0.3356	-0.3222	2.8526
2011m4	356	0.9996	0.3317	-0.8994	2.2297
2011m5	358	1.0049	0.4444	-0.6642	2.6530
2011m6	364	1.0038	0.4625	-1.7096	2.8372
2011m7	368	0.9994	0.3907	-0.7089	2.2265
2011m8	370	1.0027	0.3743	-0.2142	1.8051
2011m9	372	1.0004	0.2491	-0.4258	2.2901
2011m10	372	0.9998	0.2919	-0.4292	2.3645
2011m11	372	1.0014	0.2705	-0.1706	1.8448
2011m12	375	1.0007	0.2811	0.1267	1.9797
2012m1	376	1.0005	0.2145	-0.0066	1.6531
2012m2	376	1.0004	0.3387	-0.6246	2.1899
2012m3	380	0.9995	0.3164	-0.6481	1.9371
2012m4	382	1.0005	0.5822	-2.6020	3.0269
2012m5	386	0.9950	0.4483	-0.7992	2.7393
2012m6	396	1.0015	0.5074	-1.3980	4.9665
2012m7	400	1.0188	0.4339	-2.2983	3.1622
2012m8	405	0.9987	0.2922	-0.0700	2.6124
2012m9	409	1.0019	0.3425	-0.2210	2.7386
2012m10	411	1.0002	0.4898	-3.0403	3.0608
2012m11	411	0.9966	0.4779	-0.9497	4.0646
2012m12	415	0.9988	0.4618	-0.5239	4.0144
2013m1	417	0.9999	0.3631	-0.9000	2.5972
2013m2	417	0.9961	0.5503	-1.4886	4.0680
2013m3	418	0.9997	0.5261	-1.7796	3.9590
2013m4	417	1.0045	0.3410	-1.1011	3.6248

Month	Observation	Mean	S.D.	Min	Max.
2013m5	419	1.0003	0.1978	0.2584	2.1051
2013m6	421	1.0004	0.1401	0.4714	1.3617
2013m7	424	0.9987	0.1490	0.3788	1.6130
2013m8	421	1.0032	0.2968	-0.3982	2.5870
2013m9	424	0.9980	0.1851	0.4475	1.7028
2013m10	417	0.9994	0.3050	-0.2432	2.1239
2013m11	426	1.0014	0.3239	-0.4911	2.3177
2013m12	431	1.0030	0.3382	-0.1162	2.1110
2014m1	428	0.9980	0.3529	-0.9543	2.5746
2014m2	429	1.0048	0.3592	-0.5933	2.2685
2014m3	432	0.9957	0.3607	-0.7268	2.2924
2014m4	429	0.9952	0.2983	0.1583	2.4910
2014m5	426	1.0046	0.3211	-0.9271	2.0596
2014m6	429	1.0010	0.3254	-1.0516	2.0076
2014m7	429	1.0054	0.4148	-0.8928	4.6297
2014m8	427	1.0030	0.2708	-0.8110	2.3429
2014m9	428	1.0059	0.3156	-0.0339	3.2508
2014m10	422	0.9988	0.3075	-0.1593	3.1608
2014m11	423	0.9994	0.5748	-3.1904	4.4236
2014m12	433	0.9997	0.1976	0.0290	1.6379
2015m1	432	1.0022	0.2897	-0.0435	2.1330
2015m2	433	1.0005	0.2001	0.2344	2.0223
2015m3	436	1.0008	0.2889	-0.0294	2.0640
2015m4	432	1.0040	0.4010	-0.6326	3.7975
2015m5	424	1.0025	0.4180	-1.5907	2.0850
2015m6	429	1.0027	0.4244	-0.6182	2.1280
2015m7	428	1.0043	0.4953	-0.7254	3.1283
2015m8	427	1.0022	0.3464	-1.3740	2.1276
2015m9	421	0.9956	0.5491	-1.2478	3.6816
2015m10	426	0.9963	0.3306	-0.1066	2.4552
2015m11	425	1.0019	0.4248	-1.0053	2.3436
2015m12	430	0.9987	0.6442	-3.0079	3.0445

Month	Observation	Mean	S.D.	Min	Max.
2016m1	425	0.9993	0.5501	-1.9872	3.8279
2016m2	428	0.9991	0.5998	-3.4635	3.4978
2016m3	427	0.9976	0.6719	-1.5790	7.8582
2016m4	424	0.9989	0.4627	-1.4617	3.4083

APPENDIX B: Selection Order Criterion

Table B1. Lag selection order criterion for volatility and herding

lag	LL	LR	df	p	FPE	AIC	HQIC	SIC
0	-26.5094				0.0048	0.3334	0.3484	0.3702
1	62.3244	177.67*	4	0.0000	0.0018*	-0.6588*	-0.6140*	-0.5485*
2	63.3699	2.0909	4	0.7190	0.0018	-0.6242	-0.5497	-0.4405
3	67.5658	8.3919	4	0.0780	0.0018	-0.6265	-0.5221	-0.3693
4	70.1303	5.1290	4	0.2740	0.0019	-0.6097	-0.4755	-0.2790
5	71.1228	1.9850	4	0.7390	0.0019	-0.5745	-0.4105	-0.1703
6	72.5071	2.7685	4	0.5970	0.0020	-0.5439	-0.3501	-0.0663
7	72.6241	0.2341	4	0.9940	0.0021	-0.4985	-0.2749	0.0526
8	73.6764	2.1045	4	0.7170	0.0022	-0.4641	-0.2106	0.1606
9	75.9209	4.4889	4	0.3440	0.0022	-0.4435	-0.1602	0.2546
10	77.5795	3.3173	4	0.5060	0.0023	-0.4161	-0.1030	0.3555
11	80.4476	5.7361	4	0.2200	0.0023	-0.4029	-0.0600	0.4422
12	83.1576	5.4202	4	0.2470	0.0023	-0.3878	-0.0151	0.5308
13	87.1941	8.0730	4	0.0890	0.0023	-0.3882	0.0143	0.6039

Sample Period: 2002m2 - 2016m4
Number of Observations: 171

Table B2. Lag selection order criterion for market return and herding

lag	LL	LR	df	p	FPE	AIC	HQIC	SIC
0	660.4300				0.00000160	-7.7009	-7.6860	-7.6642
1	728.0790	135.3000	4	0.0000	0.00000074	-8.4454*	-8.4006*	-8.3351*
2	730.9810	5.8040	4	0.2140	0.00000075	-8.4325	-8.3580	-8.2488
3	731.4950	1.0288	4	0.9050	0.00000078	-8.3918	-8.2874	-8.1345
4	733.9160	4.8420	4	0.3040	0.00000079	-8.3733	-8.2391	-8.0426
5	738.9920	10.152*	4	0.0380	0.00000078	-8.3859	-8.2219	-7.9817
6	739.4280	0.8725	4	0.9280	0.00000082	-8.3442	-8.1504	-7.8665
7	743.4750	8.0923	4	0.0880	0.00000082	-8.3447	-8.1211	-7.7936
8	745.5240	4.0985	4	0.3930	0.00000083	-8.3219	-8.0685	-7.6973
9	747.4230	3.7973	4	0.4340	0.00000086	-8.2973	-8.0141	-7.5992
10	748.6920	2.5389	4	0.6380	0.00000088	-8.2654	-7.9523	-7.4938
11	750.6870	3.9897	4	0.4070	0.00000091	-8.2420	-7.8990	-7.3968
12	753.1880	5.0025	4	0.2870	0.00000092	-8.2244	-7.8517	-7.3058
13	757.3100	8.2436	4	0.0830	0.00000092	-8.2259	-7.8233	-7.2337

Sample Period: 2002m2 - 2016m4
Number of Observations: 171

Table B3. Lag selection order criterion for market direction and herding

lag	LL	LR	df	p	FPE	AIC	HQIC	SIC
0	-29.123				0.0049	0.3640	0.3789	0.4008
1	31.1312	120.51	4	0.0000	0.0026*	-.0.2939*	-.02492*	-0.1837*
2	32.7009	3.1394	4	0.5350	0.0026	-0.2655	-0.1910	-0.0818
3	35.6118	5.8216	4	0.2130	0.0027	-0.2528	-0.1484	0.0044
4	36.5731	1.9226	4	0.7500	0.0028	-0.2172	-0.0830	0.1135
5	38.7924	4.4386	4	0.3500	0.0028	-0.1964	-0.0324	0.2078
6	41.2022	4.8196	4	0.3060	0.0029	-0.1778	0.0160	0.2999
7	42.5662	2.7281	4	0.6040	0.0030	-0.1470	0.0767	0.4042
8	45.1415	5.1504	4	0.2720	0.0030	-0.1303	0.1232	0.4943
9	45.6125	0.94207	4	0.9180	0.0031	-0.0890	0.1942	0.6091
10	48.0744	4.9239	4	0.2950	0.0032	-0.0710	0.2421	0.7006
11	50.3997	4.6505	4	0.3250	0.0033	-0.0515	0.2915	0.7937
12	52.394	3.9887	4	0.4080	0.0033	-0.0280	0.3447	0.8906
13	60.833	16.878*	4	0.0020	0.0032	-0.0799	0.3226	0.9122

Sample Period: 2002m2 - 2016m4

Number of Observations: 171