Marmara Üniversitesi İktisadi ve İdari Bilimler Dergisi • Cilt: 44 • Sayı: 1 • Haziran 2022, ISSN: 2587-2672, ss/pp. 36-52
DOI: 10.14780/muiibd.1135455

ARAŞTIRMA MAKALESİ / RESEARCH ARTICLE

TESTING FOR HERD BEHAVIOR IN BORSA ISTANBUL DURING THE COVID-19 PANDEMIC

COVID-19 KÜRESEL SALGINI SIRASINDA BORSA İSTANBUL'DA SÜRÜ DAVRANIŞININ TEST EDİLMESİ

Devrim YALÇIN[*]
Aslı AYBARS[**]

Abstract

The concept of herd behavior is based on the nature of decentralized acting investors' pseudo-collaborative behaviors in the market. This study investigates the herd behavior phenomenon for Borsa Istanbul (BIST) amidst the new coronavirus outbreak. The whole period is split into symmetrical two discrete one-year sub-periods considering the median date of March 11^{th}, 2020, the official announcement date of the first domestic COVID-19 case. The paper proceeds with the models based on the Cross-sectional mean absolute deviation (CSAD) and the Cross-sectional standard deviation (CSSD) test methodology to test for probable herd behavior, using daily stock closing prices of the BIST 100 index shares during the period from March 11^{th}, 2019 to March 9^{th}, 2021.
Keywords: Behavioral Finance, Market Efficiency, Time-Series Models.
JEL Classification: G02, G14, C22.

Öz

Sürü davranışı kavramı, herhangi bir merkeze bağlı olmadan hareket etmeye meyilli yatırımcıların piyasada gerçekleştirdikleri sözde koordineli veya işbirlikçi davranışlarının doğasına dayanmaktadır. Bu çalışma, yeni koronavirüs salgını sırasında Borsa İstanbul (BIST) için sürü davranış fenomenini araştırmaktadır. Tüm dönem, yerel anlamda ilk kez karşılaşılan COVID-19 vakasının resmi duyuru tarihi olan 11 Mart 2020 tarihini medyan noktası olarak dikkate alarak iki tane ayrık simetrik bir yıllık alt döneme ayrılmıştır. Makale, 11 Mart 2019 – 9 Mart 2021 dönemi boyunca BIST 100 endeksini oluşturan hisselerin günlük hisse senedi kapanış fiyatları kullanılarak, muhtemel sürü davranışını test etmek için Kesitsel ortalama mutlak sapma (CSAD) ve Kesitsel standart sapma (CSSD) test etme metodolojisine dayanan modelleri esas almak suretiyle ilerlemektedir.
Anahtar Kelimeler: Davranışsal Finans, Piyasa Etkinliği, Zaman Serisi Modelleri.
JEL Sınıflandırması: G02, G14, C22.

* PhD, Marmara University, Institute of Banking and Insurance (alma mater), Istanbul. E-mail: devrimyalcin@hotmail.com, ORCID: 0000-0002-0017-2959

** Assoc. Prof., Marmara University, Business Administration Faculty, Istanbul. E-mail: asli.aybars@marmara.edu.tr, ORCID: 0000-0002-7899-2367

Makale Gönderim Tarihi: 04.01.2022
Yayına Kabul Tarihi: 22.06.2022

1. Introduction

Traditional finance theories have been built on the rational expectations of investors who are hypothetically capable of accessing all available information about the markets. The arguments of the rationality of each trader's behavior in Lucas (1972) and that of all the available information fully reflected by prices for these *rational* agents in Fama (1970) have been considered as the backbone of contemporary financial theory of asset pricing for more than 30 years (Konstantinidis et al., 2012). However, a number of studies have been theoretically and empirically examining and criticizing the efficient market hypothesis and the rationality of investors, arguing a well-founded opposite view of irrationality instead, significantly increasing since the 1990s.

Contrary to the efficient market hypothesis, behavioral finance argues that individuals might be irrational in making decisions on investing due to psychological biases. Kahneman and Tversky's (1979) paper is considered a prominent study of behavioral finance, arguing that psychological attributes such as heuristics and biases may affect investment decisions under uncertainty as explained in Prospect Theory. The most common heuristics are representativeness, anchoring, herding, and overconfidence (Konstantinidis et al., 2012).

One of the most important phenomena that investor behavior reveals in financial markets is herd behavior. Herd behavior is the behavior of individuals acting collectively but decentralized in fact. It is defined as a kind of investment strategy based on imitating others' actions. For an investor to imitate others, the ability to observe and follow common tendencies is vital (Bikhchandani and Sharma, 2001). The thought of herd behavior reflecting the irrational response of investors rather than the outcome of rational decision-making is of particular concern in terms of asset pricing systematics (Christie and Huang, 1995). Because investors ignoring their own beliefs and mimicking the market's consensus might be exposed to inefficient prices for the transactions on investments, even if herding is wrong for all of the herd. Bikhchandani and Sharma (2001) call it a 'snowballing effect' which describes an unprofitable state for a group of investors till they decide to exit the market.

On the other hand, individuals who make similar investment decisions do not always mean herd behavior (Altay, 2008). This phenomenon indicates 'spurious herding,' primarily due to the same information sets available for 'unintentionally' taking similar investment decisions for groups when the market mostly gets efficient. Empirically distinguishing spurious herding from 'intentional' interactive herding is often tricky because of many factors influencing investment decisions (Bikhchandani and Sharma, 2001).

The major motivations for herding behavior could be categorized into three groups; imitating other investors' actions as being the best approach in uncertain circumstances, rewarding investors by their relative performance depending on being in the majority, and being in danger of having gone out of play if they are in the minority (Persaud, 2000). Whatever the reason is, since herd behavior increases the systemic fragility or risk in the market, it is crucial to evaluate whether there exists a herding formation or not and how to measure it if there exists.

Throughout this paper, we examine herd behavior in the Turkish stock exchange, namely Borsa Istanbul, along the lines of Christie and Huang (1995) (hereafter referred to as CH), Chang, Cheng, and Khorana (2000) (2000) (hereafter referred to as CCK), and Lee, Chen, and Hsieh (2013) models. These methodologies are technically based on the idea of measuring the deviations from the majority. While applying this technique, it is expected that lower individual return differences around the mean value of market return indicate a tendency for convergence. Therefore, the magnitude of these individual scatterings from the aggregated market is the essential measure to test the herding formation for the selected sample during a period under stress.

2. Literature

In the behavioral finance literature, there are a number of methodologies modeling herd behavior tendencies in stock exchange markets. Herd behavior is simply about influences on investors who mimic the investment decisions of other investors. The prominent types to examine herd behavior could be categorized into market-wide herd behavior, institutional herd behavior, and mutual fund herd behavior (Dewan and Dharni, 2019). This paper mainly studies the standard type of behavior for investors towards the common market views and trading a specific stock more or less simultaneously, which defines the market-wide herd behavior.

One of the pioneer studies on herd behavior, Scharfstein and Stein (1990), examine the forces that influence the investors to follow the majority. According to their 'learning' model, managers imitate other managers under certain circumstances. They assume that there are two types of managers, *smart* ones and *dumb* ones, which are initially not identified by themselves or the labor market. Depending on every investment decision, the managerial labor market updates its perception of these managers based on their profitability and similarity to others. Among these criteria, the latter is important since it includes the *sharing-the-blame* effect. If one manager imitates others, this suggests to the labor market that he is more likely to be smart; otherwise, in a contrarian position to the majority, he is more likely to be dumb. Consequently, in this model, managers ignore their knowledge, thoughts, and beliefs; they herd on others' investment decisions for the sake of sharing the blame.

In the model set up by Banerjee (1992), the underlying rationale is that the investors' decisions may reflect information. According to his model, decisions made by others make each investor's decision less responsive to her own information and hence less informative to others. The decision rules chosen by optimizing individuals are characterized by herd behavior, indicating that the resulting equilibrium is inefficient.

Bikhchandani, Hirshleifer and Welch (1992) developed a model of informational cascades examining the dynamics of imitative decision processes. Their research is about how likely it is that a cascade and a *wrong* cascade occur. They argue that localized conformity of behavior can be explained by short-lived phenomena such as fashions and fads.

To test for the presence of herd behavior, the paper of Christie and Huang (1995) using the cross-sectional standard deviation of returns, is a milestone in measuring investors' common acts.

They examine the investment behavior of individuals in the stock market under various market circumstances. They argue that if individuals suppress their own thoughts in investing during extreme fluctuating periods of the market, they tend to converge due to decreasing cross-sectional standard deviations.

Chang, Cheng, and Khorana (2000) enhance the CH model using a non-linear regression specification based on the cross-sectional *absolute* deviation of returns instead of standard deviations. They also extend this practice to both developed and developing countries to examine herd formation. They show that macroeconomic information rather than firm-specific information impacts individuals' behavior in investing.

Following the approach of Chang et al. (2000), another paper by Lee et al. (2013) measures industry herding formation by dividing market states into *bullish* and *bearish* kinds since herd behavior is particularly worthy of exploration in emerging markets. Their findings prove the presence of industry herding formation in China's A-share markets, in which qualified foreign institutional investors can purchase shares and trade.

Several researchers have applied the CH model and CCK models to study various stock exchange markets as a popular method of examining herd behavior since the early 2000s. Demirer and Kutan (2006) examine the presence of herd behavior in Shangai and Shenzen Stock Exchanges along the lines of Christie and Huang (1995), Chang et al. (2000), and Gleason, Lee, and Mathur (2003). They use a data set consisting of daily stock returns over the 1999 to 2002 period and find no evidence of herd behavior for Chinese stock markets. Demirer, Kutan, and Chen (2010) employ two testing methodologies: the return dispersion-based models of Christie and Huang (1995) and state-space models of Hwang and Salmon (2004). They examine the Taiwanese Stock Exchange using daily returns for the period 1995–2006. According to their results of return dispersion models, the herd formation is mostly prominent for periods of market losses. The results of state-space models, on the other hand, vary in findings regarding the industries, which the researchers interpret as possibly caused by foreign investments.

Similar researches are carried out for Indian markets. Satish and Padmasree (2018) study herd behavior in the Indian stock exchange from 2003 to 2017 using the CCK model, and they do not observe any herd behavior formation. Shrotryia and Kalra (2019) empirically examine herd formation in the Indian stock exchange, using the CH model and the CCK model. Their results reveal that there is prudence and efficiency in the stock market instead of herd formation from 2006 to 2018.

Various studies incorporate both CH and CK models to empirically examine the possible impact of the Covid-19 pandemic on market-wide herd behavior. Chang et al. (2020) comparatively examine the influence of the global financial crisis (2007-2009), the coronavirus crises of SARS (2003), and the ongoing Covid-19 (2020) pandemic, show that the herd behavior is more likely during extremely high oil returns after the global financial crisis and the investors are more sensitive to asset losses, so investors' panic led them to sell their assets unwisely. Espinosa – Méndez and Arias (2021) find robust evidence that the Covid-19 has increased herd behavior in European capital markets by using a broad range sample of CAC 40 (Paris), DAX 30 (Frankfurt), FTSE MIB (Milan), FTSE 100 (London), and Ibex 35 (Madrid) stock exchanges over a long period from the beginning of 2000 to the middle of 2020.

Examining the effect of the Covid-19 pandemic on investors' herd behavior in a set of 49 global stock markets including emerging stock markets and thee European PIIGS stock markets, Bouri et al. (2021) show a strong relationship between herding formation and uncertainty in stock markets induced by the recent novel coronavirus pandemic. They conclude a direct link between the most recent pandemic and investors' behavior in financial markets, highlighting the role of disaster risks such as Covid-19 as a potential driver of behavioral patterns in financial markets.

Ozkan (2021) investigates the impact of the Covid-19 outbreak on stock market efficiency for six hard-hit developed countries from July 2019 to January 2021 and shows that the stock markets of these countries deviated from market efficiency in some periods during the recent novel pandemic.

There are a number of papers examining the presence of herd behavior in the Turkish stock exchange. Doğukanlı and Ergün (2015) examine the existence of herd behavior in Borsa İstanbul using the Hwang and Salmon (2004) methodology, which is based on detecting and measuring herd formation by cross-sectional dispersion of the factor sensitivity of assets. In conclusion, they observe that BIST investors might act like her formation in some periods, in the data span of 2000 to 2011.

Cakan and Balagyozyan (2014) look for evidence of investor herding in the Turkish banking sector by applying the CCK model to daily stock returns and finding evidence of herd behavior from 2007 to 2012. They also find that herding is only present when the market rises.

Solakoglu and Demir (2014) examine the sentimental herding in Borsa İstanbul using a state-space model for two distinct groups of investors. They find no evidence of herding by the BIST 30 investors from 2000 to 2013, whereas they find sentimental herding for the Second National Market (SNM), invested mainly by domestic investors. They also find that the SNM investors act herding persistently and independently from market fundamentals in three stages: evidence of herding in 2000–2004, the no-herding calm period in 2005–2008, and a volatile adverse herding pattern in 2009–2013.

Altunoz (2018) investigates the presence of herding effect in the Turkish stock exchange through the CH model and the CCK model dividing the period from 1998 to 2016 into two sub-periods; the middle point is the beginning of 2006. According to the findings, herd behavior intensity is mainly in the first sub-period when the market rises.

Erdogan (2021) examines beta herding in the Covid-19 era in Borsa Istanbul based on the state-space utilizing cross-sectional volatility of beta coefficients between 2010-2020 and finds intentional herding among investors in Borsa Istanbul. It means that the investors herd after observing others rather than following the public information.

Erdogan (2022) examines the participation banks' herd behavior in their lending decisions in Turkey by employing the Lakonishock, Shleifer, and Vishny (LSV) and Frey, Herbst, and Walter (FHW) herding measures during the period from 2010 to 2020 and shows the evidence of significant herding formation for the entire sample.

3. Research

3.1. Rationale

Depending on the perceptional standing of the investors at the crisis moment, it might be said that the COVID-19 pandemic has wreaked havoc on the global financial markets, especially on the stock markets. This is due to the common herd effect in terms of behavioral anomalies, which may conditionally or unconditionally cause bubbles and anti-bubbles. Therefore, it is first aimed to investigate whether there exists any herd behavior in the main index (the BIST 100) and sub-indexes of Borsa Istanbul, and if so, to then make clear the breakpoint conditions. Furthermore, on the condition that the degree of herd behavior among stock markets is measured, it might be possible to indirectly test and interpret the effectiveness of the efficient market hypothesis.

3.2. Methodology

As the starting point of the study, we obtain the simple (rate of) return of stocks for each day of the whole period of the sample as in the following definitive expression (Steland, 2012, p. 7):

$$R_{it} = \frac{P_{it} - P_{i(t-1)}}{P_{i(t-1)}} \tag{1}$$

where R_{it} and P_{it} are the simple return, and the closing price for the stock *i* on the day *t*, respectively. Comparing the simple return formula with the logarithmic return formula, there is a rationale for preferring the former over the latter. Despite the fact that distributions of the simple returns and the logarithmic returns are really close to each other (especially when the simple return's value is near zero) (Miskolczi, 2017), the continuously compounded returns are not additive across a portfolio (Brooks, 2019), because the logarithm of a sum is not exactly equal to the sum of a logarithm which is a non-linear transformation. This mathematical fact is well-known as Jensen's inequality (Needham, 1993).

Using simple return as the cross-sectional arithmetic average for the stocks of the sample, the aggregated market return can be calculated as follows:

$$\bar{R}_t = \frac{\sum R_{it}}{N} \tag{2}$$

where $\bar{R}_t$, the cross-sectional average of the *N* returns of the portfolio, denotes the market return for the aggregated components of the BIST 100 index on the day *t*.

To measure the dispersion of stock returns, we follow Christie and Huang (1995) model (hereafter referred to as CH) and its extended version Chang, Cheng and Khorana (2000) model (hereafter referred to as CCK).

According to the CH model, the cross-sectional standard deviation of stock returns, referred to as CSSD, is measured by the following definition (Christie and Huang, 1995):

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{it}-\bar{R}_t)^2}{N-1}} \tag{3}$$

where $CSSD_t$, the degree to which stock returns tend to act (fall or rise) in concert with the portfolio return is the main proxy for herd behavior. The CH model argues that "the aggregated dispersion is expected to be low under the circumstance of herding behavior" because the investors would avoid individuals acting on their own potential outlier decisions. However, since the common consequences of both the differential predictions of rational asset pricing models and the presence of herd behavior tend to induce the extreme tails of the aggregated dispersion, to distinguish the significance of it, the CH model performs the following empirical specification:

$$CSSD_t = \alpha + \beta_L D_t^L + \beta_U D_t^U + \varepsilon_t \tag{4}$$

where D_t^L and D_t^U are dummy variables equal to 1 if the market return on day *t* lies in the extreme lower tail and upper tail of the return distribution, respectively, and they are equal to 0 otherwise. The underlying rationale of the dummy variables above is to capture the differences between relatively extreme down and up situations within investing behaviors.

In equation (4), if β_L and β_U are statistically significant and negative, these coefficients would indicate herd behavior. Otherwise, if these parameters are statistically significant and positive, it might be concluded that these coefficients are the result of rational asset pricing models. The α coefficient denotes the non-extreme region in the dispersion of the sample. And ε_t is the general error term, so-called disturbance.

According to the CCK model, the cross-sectional absolute deviation of stock returns, referred as CSAD, is measured by the following expression (Chang et al., 2000):

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{it}-\bar{R}_t| \tag{5}$$

where $CSAD_t$ is the proxy for the dispersion measure of stock returns around $\bar{R}_t$, the cross-sectional average market return on the day *t*. Chang et al. (2000) show that the linear and increasing relation between dispersion and market return as provided by rational asset pricing models will no longer hold under the circumstance of the presence of herd behavior in the market since market participants would tend to mimic aggregate market behavior while suppressing or even ignoring their own individual investing decisions. Hence, if there exists herd behavior in the market, the relation transforms into a non-linear form as in the following specifications:

$$CSAD_t^{UP} = \alpha + \gamma_1^{UP}|\bar{R}_t^{UP}| + \gamma_2^{UP}(\bar{R}_t^{UP})^2 + \varepsilon_t \tag{7}$$

$$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}|\bar{R}_t^{DOWN}| + \gamma_2^{DOWN}(\bar{R}_t^{DOWN})^2 + \varepsilon_t \tag{8}$$

where $CSAD_t^{UP}$ and $CSAD_t^{DOWN}$ are the values of cross-sectional absolute deviation, $CSAD_t$, when the market is up ($\bar{R}_t > 0$) and down ($\bar{R}_t < 0$), respectively, on the day *t*. In both equations (7) and (8), $|\bar{R}_t^{UP}|$ and $|\bar{R}_t^{DOWN}|$ are the absolute values of market return to account for the magnitude of market movement on average considering their coefficients γ_1^{UP} and γ_1^{DOWN}. $(\bar{R}_t^{UP})^2$ and $(\bar{R}_t^{DOWN})^2$ as the essential terms reflecting non-linear feature of herd behavior in the two similar equations above are the squared values of the average market return. The non-linear terms' coefficients γ_2^{UP} and γ_2^{DOWN} indicate the presence of a non-linear market model, which are expected to be negative if there exists herd behavior. To be precise, the non-linearity exists only if γ_2 has statistically significant and negative value due to regressions of (7) and (8). Chang et al. (2000) developed a two-way-model system because of the potential asymmetric herding behavior phenomenon. Challenging the CAPM assumption of linearity, Chang et al. (2000) empirically followed the essential way of non-linearity to the market timing model proposed by Treynor and Mazuy (1966). They argue that the characteristic line representing the volatility between the fund rate of return and the market rate of return will no longer be straight if fund management has correctly anticipated the market more often than not (Treynor and Mazuy, 1966).

Lee et al. (2013) modified the CCK model with a measure of dispersion as in the following.

$$CSAD_t = \alpha + \gamma_1\bar{R}_t + \gamma_2|\bar{R}_t| + \gamma_3\bar{R}_t^2 + \varepsilon_t \tag{9}$$

where $CSAD_t$ is, again, the measure of return dispersion of the stocks in the selected portfolio, $|\bar{R}_t|$ is the absolute value of market return to account for the magnitude of market movement on average, $\bar{R}_t^2$ is the variable to capture the non-linear relationship considering its coefficient negative (i.e. $\gamma_3 < 0$), which is the same rationale based on the CCK model. Lee et al. (2013) suggested adding the term $\gamma_1\bar{R}_t$ into the original CCK regressions described in Equations (7) and (8), to consider asymmetric behavior under different market circumstances.

3.3. Data

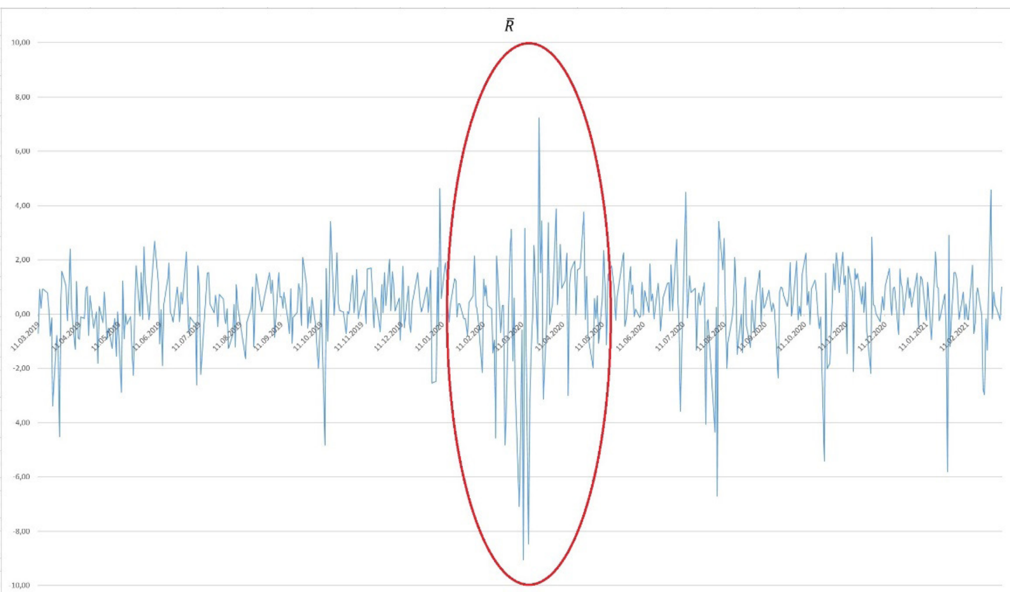
The dataset used in the study consists of the BIST 100 shares. Here we focus on the BIST 100 index's components since it is the most commonly considered national financial market index in Turkey. The BIST 100 index consists of 100 shares quoted in BIST, based on its own weighting method. All the data are obtained in daily frequency from the web portal www.investing.com. The descriptive statistics of data used during the study are summarized in Table 1 below.

Table 1. Descriptive Statistics

Period	Expected Return	Variance	$\bar{R}_{min}$	$\bar{R}_{med}$	$\bar{R}_{max}$
11.03.2019–09.03.2021 (Whole span: 500 days)	0.0005	2.6271	-9.0557	0.3450	7.2215
11.03.2019–10.03.2020 (Pre-term: 250 days)	0.1068	1.9824	-7.0823	0.2488	4.6269
11.03.2020–09.03.2021 (Post-term: 250 days)	0.3467	3.1405	-9.0557	0.4039	7.2215

Table 1 reports the descriptive statistics of the aggregated components of the BIST 100 index, where $\bar{R}_{min}$, $\bar{R}_{med}$ and $\bar{R}_{max}$ denote the minimum, median, and maximum values of the cross-sectional average on each day in the period considered, respectively. The minimum and maximum values are observed in the post-term, which is between the official announcement date of the first case in the country and the last date of all observations. This fact of the sample indicates that the returns for the BIST 100 components have most fluctuated since the first COVID-19 case announcement. Hence, the variance of the second period of observations is greater than that of the first period. The expected return of the second period is the greatest value, concordantly with the risk, as a matter of course. Graph 1 represents the course of the average daily return for the portfolio consisting of equally-weighted shares of the BIST 100 components.

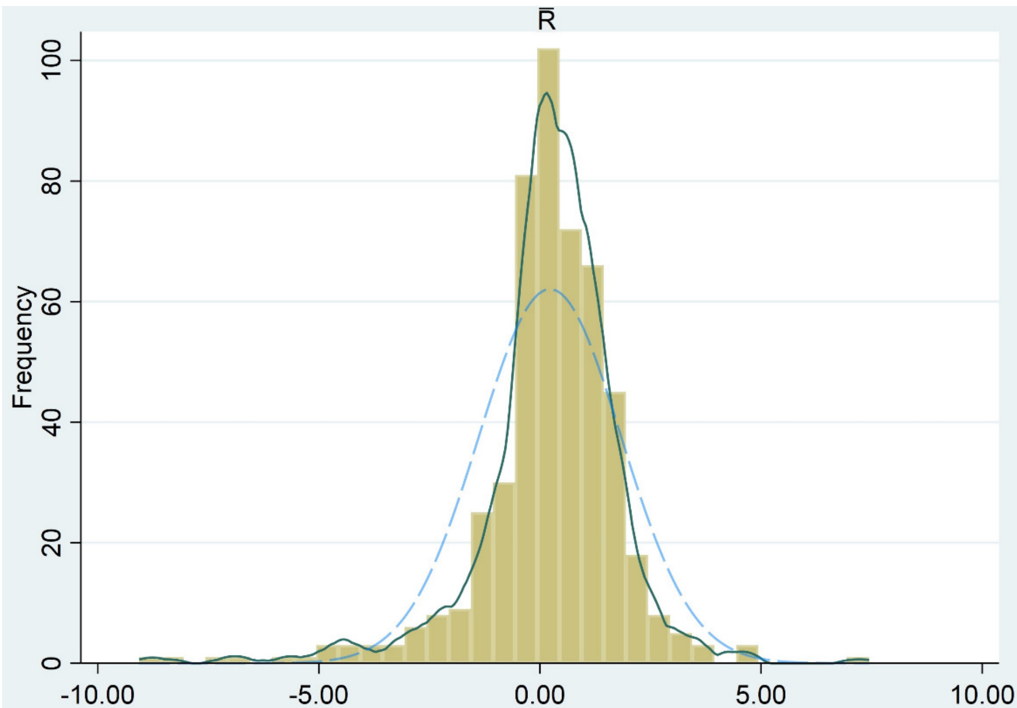
Graph 1. Equally-weighted market return ($\bar{R}_t$) for the BIST 100 index components



According to Graph 1, the equally-weighted market return (*i.e.,* the cross-sectional average of the BIST 100 component shares' return) on the day *t*, referred to as $\bar{R}_t$, has the most fluctuating period, which has the biggest wavelength, at around the middle of the data span observed. To be precise, there is a big crash – namely minus 9 percent in a day – in the average return of the BIST 100 components' equally weighted portfolio just after the official announcement date of the first case, which is March 11th, 2020. Therefore, it is an obvious fact that the share prices of the BIST 100 index components are affected by the outbreak news in the country.

The frequency distribution of the daily equally-weighted market returns ($\bar{R}_t$) for the BIST 100 index components over the whole period considered (from March 11th, 2019 to March 9th, 2021) is charted as the histogram in Graph 2. Focusing on Graph 2, we see the frequency distribution curve for the selected sample's daily average market returns ($\bar{R}_t$), compared with the dashed curve of normal distribution.

Graph 2. Frequency distribution of the daily equally-weighted market returns ($\bar{R}_t$) for the BIST 100 index components over the whole period.

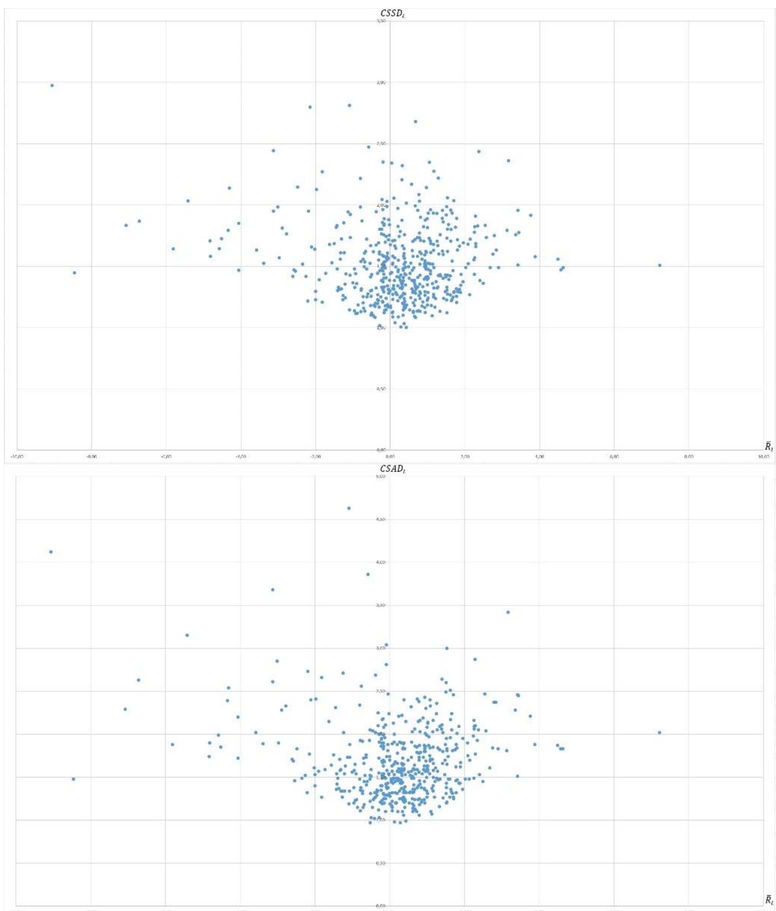


In the finance literature, the extreme market movements are categorized into two percentile groups, the extreme 1% and extreme 5% of distribution tail, among the market returns. According to the frequency distribution of the daily equally-weighted market returns ($\bar{R}_t$) for BIST 100 index components over the whole period of 500 days, in Graph 2, there are 11 days and 51 days representing the extreme movements in the market under the two criteria restricted by 1% and 5% of the tail, respectively. As seen, the average daily returns of the market are mostly positive. To be precise, in the 312 of among 500 days, daily average market return occurred as greater than zero. These positive valued days in terms of the market's average return consist of 152 pre-term and 160 post-term days.

3.4. Findings

The relationships between the daily cross-sectional standard deviation and the equally-weighted market return $(CSSD_t - \bar{R}_t)$ and between the daily cross-sectional absolute deviation and the equally-weighted market return $(CSAD_t - \bar{R}_t)$ for the BIST 100 index components over the whole period considered (from March 11th, 2019 to March 9th, 2021) are plotted as the scattering diagram in Graph 3, respectively.

Graph 3. The scattering plots of $CSSD_t - \bar{R}_t$ and $CSAD_t - \bar{R}_t$ dispersions.



Equation 4 is run using three criteria to define extreme price movements of the market under bullish (rising) and bearish (declining) conditions. The dummy variables modified by three percentiles are used to estimate the differences in the behavior of stock investors for the lower and the upper tails of the daily average market returns ($\bar{R}_t$) scaled in the same percent criterion to determine whether the typical behavior is of herding or based on the rational pricing model. Table 2 reports the findings of the CH model upon extreme tails of $\bar{R}$.

Table 2. The CH model upon extreme tails of $\bar{R}$

Model structure: $CSSD_t = \alpha + \beta_L D_t^L + \beta_U D_t^U + \varepsilon_t$					
11.03.2019 – 09.03.2021: The whole span of 500 days					
1% of tail			**5% of tail**		
$\alpha^{1\%}$	$\beta_L^{1\%}$	$\beta_U^{1\%}$	$\alpha^{5\%}$	$\beta_L^{5\%}$	$\beta_U^{5\%}$
1.51*** *(109.33)*	0.45*** *(3.61)*	0.01 *(0.06)*	1.49*** *(105.66)*	0.31*** *(5.16)*	0.21*** *(3.44)*
11.03.2019 – 10.03.2020: Pre-term of 250 days					
1% of tail			**5% of tail**		
$\alpha^{1\%}$	$\beta_L^{1\%}$	$\beta_U^{1\%}$	$\alpha^{5\%}$	$\beta_L^{5\%}$	$\beta_U^{5\%}$
1.40*** *(73.70)*	0.31* *(1.81)*	0.20 *(1.18)*	1.37*** *(72.00)*	0.34*** *(4.21)*	0.21** *(2.56)*
11.03.2020 – 09.03.2021: Post-term of 250 days					
1% of tail			**5% of tail**		
$\alpha^{1\%}$	$\beta_L^{1\%}$	$\beta_U^{1\%}$	$\alpha^{5\%}$	$\beta_L^{5\%}$	$\beta_U^{5\%}$
1.63*** *(93.62)*	0.47*** *(2.95)*	-0.12 *(-0.74)*	1.61*** *(88.71)*	0.27*** *(3.57)*	0.10 *(1.36)*

* 10%, ** 5%, *** 1% significance levels, respectively. *(t-statistics in parentheses)*

The findings summarized in Table 2 are the estimates of the CH model coefficients expressed by the regression Equation 4 in bi-class (1% and 5%) extreme tails for the BIST 100 index components during the selected data span categorized into three intervals, which are whole period, pre-term, and post-term according to the potential herd behavior beginning due to the disease outbreak.

The CH model has two distinguishing coefficients estimated by the regression, β_L, and β_U as the slopes of D^L and D^U variables, respectively. The findings obtained show no estimates of the CH model coefficients providing herd behavior for the sample at the 5% level of statistical significance. As readily seen in Table 2, the statistically significant coefficients for both the extreme low and the extreme high tail group of share returns are positive.

Equations 7 and 8 of the CCK model are designed by splitting the daily average market returns ($\bar{R}_t$) into two groups with regard to their values are positive or negative. Running these equations, we obtain the empirical findings in Table 3 below.

Table 3. The CCK model concerning $R_t > 0$ or $R_t < 0$

Model structure: $CSAD_t^{UP} = \alpha + \gamma_1^{UP}\lvert\bar{R}_t^{UP}\rvert + \gamma_2^{UP}(\bar{R}_t^{UP})^2 + \varepsilon_t$ $CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}\lvert\bar{R}_t^{DOWN}\rvert + \gamma_2^{DOWN}(\bar{R}_t^{DOWN})^2 + \varepsilon_t$					
11.03.2019 – 09.03.2021: The whole span of 500 days					
Up ($\bar{R}_t > 0$)			**Down** ($\bar{R}_t < 0$)		
α	γ_1^{UP}	γ_2^{UP}	α	γ_1^{DOWN}	γ_2^{DOWN}
1.42*** *(35.57)*	0.27*** *(5.58)*	-0.03** *(-2.46)*	1.59*** *(27.81)*	0.11* *(1.79)*	0.00 *(0.47)*
11.03.2019 – 10.03.2020: Pre-term of 250 days					
Up ($\bar{R}_t > 0$)			**Down** ($\bar{R}_t < 0$)		
α	γ_1^{UP}	γ_2^{UP}	α	γ_1^{DOWN}	γ_2^{DOWN}
1.38*** *(38.83)*	0.04 *(0.76)*	0.01 *(0.77)*	1.29*** *(34.41)*	0.15*** *(3.29)*	6.62 *(0.01)*
11.03.2020 – 09.03.2021: Post-term of 250 days					
Up ($\bar{R}_t > 0$)			**Down** ($\bar{R}_t < 0$)		
α	γ_1^{UP}	γ_2^{UP}	α	γ_1^{DOWN}	γ_2^{DOWN}
1.55*** *(25.66)*	0.33*** *(5.10)*	-0.04*** *(-3.16)*	1.86*** *(20.73)*	0.15 *(1.61)*	0.00 *(-0.36)*

* 10%, ** 5%, *** 1% significance levels, respectively. *(t-statistics in parentheses)*

Table 3 estimates that the parameter γ_2^{UP} is statistically significant and negative for the whole span (of 500 days) and the post-term (of 250 days) only when the daily average market returns are positive. Since the non-linear variable, the square of daily average market return distinguishes whether or not there exists herd behavior for the selected sample and period, we conclude that there exists herd behavior when daily average market returns are greater than zero for the whole and second periods. On the other hand, focusing on the right-hand side of Table 3, the quadratic relation parameters are not statistically significant for all periods considered. Therefore, we reject the herd behavior hypothesis when the daily average market return goes down. This finding supports the alternative hypothesis that the investors would rather go by the rational asset pricing model during the market's depressing (or stressing) periods.

Lee et al. (2013) modified the CCK model by adding the term $\bar{R}_t$ as in Equation 9 to consider the asymmetric behavior. Table 4 reports the findings for the modified CCK model.

Table 4. The modified CCK model by Lee et al. (2013)

Model structure: $CSAD_t = \alpha + \gamma_1 \bar{R}_t + \gamma_2 \lvert \bar{R}_t \rvert + \gamma_3 \bar{R}_t^2 + \varepsilon_t$			
11.03.2019 – 09.03.2021: The whole span of 500 days			
α	γ_1	γ_2	γ_3
1.51*** *(46.48)*	-0.01 *(-.082)*	0.17*** *(4.61)*	0.00 *(-0.75)*
11.03.2019 – 10.03.2020: Pre-term of 250 days			
α	γ_1	γ_2	γ_3
1.34*** *(53.73)*	-0.01 *(-1.13)*	0.10*** *(2.88)*	0.01 *(0.82)*
11.03.2020 – 09.03.2021: Post-term of 250 days			
α	γ_1	γ_2	γ_3
1.72*** *(34.35)*	-0.04** *(-2.06)*	0.21*** *(3.95)*	-0.01* *(-1.81)*

* 10%, ** 5%, *** 1% significance levels, respectively. *(t-statistics in parentheses)*

Table 4 shows that all the values of γ_3 are statistically insignificant at the 5% level, specifying that the investors of the BIST 100 shares do not indicate herd behavior during the whole and sub-periods. Only γ_3 value in the post-term is statistically significant at the 10% level, which is a controversial area to reject the rational behavior tendency for the second period of the sample.

All the results obtained from the models applied mightly indicate that the investors of the BIST 100 shares have not panicked during the selected period beginning one year before and continuing after the outbreak case.

4. Conclusion

One of the common assumptions of the traditional approach in finance is that individuals make decisions based on rational investing criteria. However, the investors do not always act rationally in terms of the essential analysis of parameters in the market. It is an obvious fact that the human being is not a flawless machine in investing. There are some tendencies in social groups to be significant in individuals' investment decisions. Therefore, individual investors and managers tend to be a part of the widely accepted decisions, especially under the circumstances potentially casting doubt on their reputation for success. This is called herd formation in the recent emerging study field of behavioral finance, which focuses on emotions, illusions, and consequently biases.

In this paper, we empirically test the presence of herd behavior formation in Borsa Istanbul's national BIST 100 index, which consists of a hundred quoted stocks, over the period considered from March 11th, 2019, to March 9th, 2021.

According to the findings of the CH model for the sample selected in the study, the investors act mostly based on their own rational thoughts and insight about the investment decisions during the market's extreme downward and upward movements while deciding to invest in the BIST 100 index components amidst the COVID-19 pandemic.

Focusing on the post-term of the sample, which is after first COVID-19 case official announcement, the findings of the model reject the herd behavior hypothesis. Therefore it might be said that the investors would rather rationally decide under extreme fluctuations in the last period for the BIST 100 shares.

The modified CCK model, which Lee et al. (2013) developed, supports the findings of the two previous models for the most expected fluctuating last period. We empirically reject the herd formation again.

In a nutshell, the herd behavior phenomenon for Borsa Istanbul amidst the new coronavirus outbreak has not been empirically observed along the line of Christie and Huang (1995), Chang et al. (2000), and Lee et al. (2013) for the specified period mentioned above. In further studies, it is possible that the sample selected would be extended into various industries concerning the main indexes of BIST.

References

Altay, E. (2008). Herding in Capital Markets: Analysis of Herding Towards the Market in ISE. *Journal of BRSA Banking and Financial Markets*, *2*(1), 27–58. https://www.bddk.org.tr/ContentBddk/BddkDergi/dergi_0003_04.pdf

Altunoz, U. (2018). Does herd behavior exist in Turkish stock markets? The case of Borsa Istanbul. Proceedings of International Academic Conferences, 8109857. DOI: 10.20472/IAC.2018.044.002

Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics*, *107*(3), 797–817. https://doi.org/10.2307/2118364

Bikchandani, S., Hirshleifer, D. & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *The Journal of Political Economy*, *100*(5), 992– 026. https://doi.org/10.1086/261849

Bikchandani, S. & Sharma, S. (2001). Herd behavior in financial markets. *IMF Staff Papers*, *47*(3), 279–310. https://doi.org/10.2307/3867650

Bouri, E., Demirer, R., Gupta, R. & Nel, J. (2021). COVID-19 Pandemic and Investor Herding in International Stock Markets. *Risks*, *9*(9), 168. https://doi.org/10.3390/risks9090168

Brooks, C. (2019). *Introductory Econometrics for Finance* (4th ed.). Cambridge University Press.

Cakan, E. & Balagyozyan, A. (2014). Herd behaviour in the Turkish banking sector. *Applied Economics Letters*, *21*(2), 75–79. https://doi.org/10.1080/13504.851.2013.842629

Chang, C. L., McAleer, M., & Wang, Y.-A. (2020). Herding behaviour in energy stock markets during the Global Financial Crisis, SARS, and ongoing COVID-19. *Renewable and Sustainable Energy Reviews*, *134*, 110349. https://doi.org/10.1016/j.rser.2020.110349

Chang, E. C., Cheng, J. W. & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance*, *24*(10), 1651–1679. https://doi.org/10.1016/S0378-4266(99)00096-5

Christie, W. G. & Huang, R. D. (1995). Following the Pied Piper: Do Individual Returns Herd around the Market?. *Financial Analysts Journal*, *51*(4), 31–37. https://doi.org/10.2469/faj.v51.n4.1918

Demirer, R. & Kutan, A. M. (2006). Does herding behavior exist in Chinese stock markets?. *Journal of International Financial Markets, Institutions and Money*, *16*(2), 123–142. https://doi.org/10.1016/j.intfin.2005.01.002

Demirer, R., Kutan, A. M. & Chen, C. D. (2010). Do investors herd in emerging stock markets?: Evidence from the Taiwanese market. *Journal of Economic Behavior & Organization*, *76*(2), 283–295. https://doi.org/10.1016/j.jebo.2010.06.013

Dewan, P. & Dharni, K. (2019). Herding behavior in investment decision making: A review. *Journal of Economics, Management and Trade*, *24*(2), 1–12. DOI: 10.9734/jemt/2019/v24i230160

Dogukanli, H. & Ergun, B. (2015). Herding in BIST: An investigation using the methodology of Hwang and Salmon. *Finans Politik ve Ekonomik Yorumlar*, *52*(603), 7–24. http://www.ekonomikyorumlar.com.tr/files/articles/152.820.006165_1.pdf

Erdogan, H.H. (2021). Beta Herding in thee Covid-19 Era: Evidence from Borsa Istanbul. *Business and Economics Research Journal*, *12*(2), 359-368. doi: 10.20409/berj.2021.326

Erdogan, H.H. (2022). Herd behavior in bank lending: Evidence from participation banks Turkey. *International Journal of Economic and Administrative Studies*, *34*, 117-128. https://doi.org/10.18092/ulikidince.940660

Espinosa-Méndez, C., & Arias, J. (2021). COVID-19 effect on herding behaviour in European capital markets. *Finance Research Letters*, *38*, 101787. https://doi.org/10.1016/j.frl.2020.101787

Fama, E.F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383–417. https://doi.org/10.2307/2325487

Gleason, K. C., Lee, C. & Mathur, I. (2003). Herding behavior in European futures markets. *Finance Letters*, *1*, 5–8.

Hwang, S. & Salmon, M. (2004). Market stress and herding. *Journal of Empirical Finance*, *11*(4), 585–616. https://doi.org/10.1016/j.jempfin.2004.04.003

Investing.com (n.d.). *BIST 100 Index Stock Prices*. Retrieved April 7, 2021, from https://www.investing.com/indices/ise-100-components

Kahneman, D. & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–292. https://doi.org/10.2307/1914185

Konstantinidis, A., Katarachia, A., Borovas, G. & Voutsa, M.E. (2012). From Efficient Market Hypothesis To Behavioural Finance: Can Behavioural Finance Be The New Dominant Model For Investing?, *Scientific Bulletin – Economic Sciences*, *11*(2), 16-26. https://ideas.repec.org/a/pts/journl/y2012i2p16-26.html

Lee, C. C., Chen, M. P. & Hsieh, K. M. (2013). Industry herding and market states: evidence from Chinese stock markets. *Quantitative Finance*, *13*(7), 1091–1113. https://doi.org/10.1080/14697.688.2012.740571

Lucas, R. E. Jr. (1972). Expectations and the neutrality of money. *Journal of Economic Theory*, *4*, 103–124. https://doi.org/10.1016/0022-0531(72)90142-1

Miskolczi, P. (2017). Note on simple and logarithmic return. Applied Studies in Agribusiness and Commerce, *11*(1-2), 127–136. doi: 10.19041/apstract/2017/1-2/16

Needham, T. (1993). A Visual Explanation of Jensen's Inequality, *The American Mathematical Monthly*, *100*(8), 768–771. https://doi.org/10.1080/00029.890.1993.11990484

Ozkan, O. (2021) Impact of COVID-19 on stock market efficiency: Evidence from developed countries. *Research in International Business and Finance*, *58*, 101445. https://doi.org/10.1016/j.ribaf.2021.101445

Persaud, A. (2000). Sending the herd off the cliff edge: The disturbing interaction between herding and market-sensitive risk management practices. *Journal of Risk Finance*, *2*(1), 59–65. https://doi.org/10.1108/eb022947

Satish, B. & Padmasree, K. (2018). An empirical analysis of herding behavior in Indian stock market. *International Journal of Management Studies*, *5*(3), 124–132. http://researchersworld.com/ijms/vol5/issue3_3/Paper_15.pdf

Scharfstein, D. S. & Stein, J. C. (1990). Herd behavior and investment. *The American Economic Review*, *80*(3), 465–479. https://www.jstor.org/stable/2006678

Shrotryia, V.K. & Kalra, H. (2019). An empirical investigation of herding in the Indian stock market. *e-Journal of Social & Behavioral Research in Business*, *10*(1), 40–53. http://ejsbrb.org/upload/e-JSBRB_4_Shrotryia_Kalra_10(1)_2019_.pdf

Solakoglu, M.N. & Demir, N. (2014). Sentimental herding in Borsa Istanbul: informed versus uninformed. *Applied Economic Letters*, *21*(14), 965–968. https://doi.org/10.1080/13504.851.2014.902015

Steland, A. (2012). *Financial Statistics and Mathematical Finance: Methods, Models and Applications*. John Wiley & Sons, Ltd.

Treynor, J. L. & Mazuy, K. (1966). Can Mutual Funds Outguess the Market? *Harvard Business Review*, *4*, 131-136.