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THE EFFECT OF INVESTOR SENTIMENT ON BORSA ISTANBUL (BIST)

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ABSTRACT

Doctoral Thesis

Doctor of Philosophy (PhD)

The Effect of Investor Sentiment on Borsa Istanbul (BIST)

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Investor sentiment is defined basically as the general feelings of optimism and pessimism levels of investors about the market. The main aim of this study is to analyze the impact of investor sentiment on Borsa Istanbul as a developing market during the crisis periods beginning from 1997 to 2017. Before investigating the probable effects of investor sentiment on stock returns, a new composite sentiment index for Borsa Istanbul was constructed by using principal component analysis (PCA). Further, three crises were detected based on the CMAX crisis indicator (1997 Asian and 1998 Russian financial crises, 2001 Turkish financial crisis, and 2008 global financial crisis), and they were separated as local and international based on their origin to analyze if the pattern of investor sentiment differs between locally and internationally originating crises.

The regression analysis was conducted to investigate the effect of investor sentiment on the future stock market returns during the determined crisis periods. The regression equations were tested for the whole period and the crisis periods separately. Moreover, the macroeconomic factors and structural breaks were included into the analysis as control variables. The results showed that investor sentiment is statistically significant and negatively related with the future BIST 100 index returns in the whole, no crisis and local crisis periods. For that reason, the presence of investor sentiment should be considered while

taking important investment decisions during these risky periods. Moreover, policy makers and domestic and foreign investors shall consider investor sentiment as an additional source of systematic risk.

Keywords: Behavioral Finance, Investor Sentiment, Stock Market, Financial Crises, Investor Sentiment Index.

ÖZET

Doktora Tezi

Yatırımcı Duyarlılığının Borsa İstanbul (BİST) Üzerindeki Etkisi

Zeliha CAN ERGÜN

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İngilizce İşletme Yönetimi Doktora Programı

Yatırımcı duyarlılığı temelde yatırımcıların piyasa hakkındaki genel iyimser ve kötümser hisleri olarak tanımlanmaktadır. Bu çalışmanın ana amacı 1997 ve 2017 arasındaki kriz dönemlerinde yatırımcı duyarlılığının gelişmekte olan bir piyasa olan Borsa İstanbul üzerindeki etkisini analiz etmektir. Yatırımcı duyarlılığının hisse senedi getirileri üzerindeki olası etkilerini incelemeden önce, Borsa İstanbul için yeni bir bileşik duyarlılık endeksi temel bileşen analizi kullanılarak oluşturulmuştur. Ayrıca, CMAX kriz göstergesine dayalı üç kriz tespit edilmiş (1997 Asya ve 1998 Rusya krizi, 2001 Türk finansal krizi ve 2008 küresel finansal krizi) ve yatırımcı duyarlılığının etkisinin yerel ve uluslararası kaynaklı krizler arasında farklılık gösterip göstermediğini saptamak amacıyla krizler yerel ve uluslararası olarak ayrılmıştır.

Belirlenen kriz dönemlerinde yatırımcı duyarlılığının gelecekteki hisse senedi getirileri üzerindeki etkisini araştırmak için regresyon analizi yapılmıştır. Regresyon denklemleri tüm dönem ve kriz dönemleri ayrılarak test edilmiştir. Ayrıca, makroekonomik faktörler ve yapısal kırılmalar analizde kontrol değişkenleri olarak yer almaktadır. Sonuçlar, yatırımcı duyarlılığının tüm dönemde, kriz olmayan dönemde ve yerel kriz olan dönemde istatistiki olarak anlamlı ve takip eden BIST 100 endeksi getirileriyle negatif olarak ilişkili olduğunu göstermiştir. Bu nedenle, bu riskli dönemlerde yatırım kararları alınırken yatırımcı duyarlılığının varlığının da göz önünde bulundurulması gerekmektedir. Buna ek olarak, politika yapıcıları ve yerli ve yabancı

yatırımcılar yatırımcı duyarlılığını ek bir sistematik risk kaynağı olarak dikkate almalıdırlar.

Anahtar Kelimeler: Davranışsal Finans, Yatırımcı Duyarlılığı, Hisse Senedi Piyasası, Finansal Krizler, Yatırımcı Duyarlılığı Endeksi.

THE EFFECT OF INVESTOR SENTIMENT ON BORSA ISTANBUL (BIST)

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ABBREVIATIONS

AAII	American Association of Individual Investors
ADF	Augmented Dickey-Fuller
AFLOW	Average Flow of All Mutual Funds
BIST	Borsa Istanbul
Bovespa	Bolsa de Valores de São Paulo, Brazilian Stock Market
CAPM	Capital Asset Pricing Model
CBOE	Chicago Board Options Exchange
CBRT	Central Bank of the Republic of Turkey
CCI	Consumer Confidence Index
CEFD	Closed-End Fund Discount
CMB	Capital Market Board
CPI	Consumer Price Index
CSD	Central Securities Depository
DJIA	Dow Jones Industrial Average
DUM	Dummy Variable for Structural Breaks
EMH	Efficient Market Hypothesis
ESI	Economic Sentiment Indicator
EV	Economic Variable
EQUITY	Share of Equity Issues in Aggregate Issues
FLOW	Mutual Fund Flows
GDP	Gross Domestic Product
II	Investors Intelligence
IMF	International Monetary Fund
IPI	Industrial Production Index
IPOs	Initial Public Offerings
ISV	Internet Search Volume
KMO	Kaiser-Meyer-Olkin
NASDAQ	National Association of Securities Dealers Automated Quotations
NAV	Net Asset Value
OECD	The Organization for Economic Co-operation and Development

OLS	Ordinary Least Squares
PCA	Principal Component Analysis
p.	Page Number
pp.	Page to Page
Prob.	Probability
R	Return of BIST 100 Index
REPO	Repo Shares in Mutual Fund Portfolios
SENT	Final Investor Sentiment Index
SEOs	Seasoned Equity Offerings
S&P 500	Standard and Poor's 500
TL	Turkish Lira
tSENT	Initial Investor Sentiment Index
Turkstat	Turkish Statistical Institute
TURN	Turnover Ratio
U.K.	United Kingdom
U.S.	United States
VAR	Vector Autoregressive Model
VIX	Option Implied Volatility Index
VOLP	Volatility Premium
VWD	Value Weighted Index of Discounts
WLS	Weighted Least Squares
XR	Exchange Rate

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INTRODUCTION

Behavioral finance criticizes the rationality assumption of classical finance theories such as Capital Asset Pricing Model (CAPM), Efficient Market Hypothesis and Fama-French Factor Models, and defends that psychological and emotional factors play a vital role in the decision-making process of investors. With the rise of the behavioral finance theories, these emotions and psychological factors are considered as another source of systematic risk in finance by the behavioral scientists which is disregarded by the classical finance theorists while measuring systematic risk (Kıyılar and Akkaya, 2016: 315).

Emotions may sometimes act as heuristic shortcuts while making decisions which enable investors to make rapid decisions by only following their emotions (Aronson, Wilson and Akert, 2009: 223). For that reason, sentiment analysis has been widely used in marketing research, and recently it has also gained an importance in financial research. Basically, investor sentiment refers to the general feelings of optimism and pessimism level of investors about the market, and it is argued that unpredictable changes in investor sentiment may affect the stock prices (Verma, Baklacı and Soydemir, 2008: 1303).

The major obstacle in researching investor sentiment is that it cannot be observed directly in the market. For that reason, researchers use some proxies which are believed to represent investor sentiment. These proxies could either be survey-based proxies, which directly measure investor sentiment such as American Association of Individual Investors (AAII) Sentiment Survey, Investors Intelligence (II) Index, etc., or they could be market-based proxies which indirectly measure investor sentiment such as closed-end fund discounts, mutual fund flows, etc. The investor sentiment literature mostly focuses on measuring sentiment by variety of proxies in various markets. Overall, the literature shows that investor sentiment has an influence on developed stock markets such as the United States (U.S.) as well as the developing stock markets such as Turkey, and this influence is generally negative on the future stock returns.

Moreover, in the literature, there is a consensus that the collective optimism and pessimism levels of investors may lead to economic crisis (Bülbül, 2008: 70; Ede, 2007: 90; Kindleberger and Aliber, 2005: 42). Along this line, however, only a few researchers such as Baur, Quintero and Stevens (1998); Bolaman and Mandacı (2014); Zouaoui, et al. (2011) analyzed the effect of investor sentiment on stock markets during the economic crisis periods. However, to the best of the author's knowledge, none of these studies investigated power and sign of this effect of investor sentiment on the stock market returns during the crisis periods. For that reason, to fill this gap, the main aim and the first contribution of this study is to analyze the impact of investor sentiment on Borsa Istanbul (BIST) as a developing market during the crisis periods beginning from 1997 to 2017.

However, before investigating the probable effects of investor sentiment on stock returns, it was crucial to select the appropriate investor sentiment proxy for Borsa Istanbul. Instead of using market-based proxies separately, using a composite sentiment index may give more accurate results. In Turkey, Kaya (2017) and Keleş, et al. (2017) constructed a sentiment index, but Kaya (2017) used annual data, and Keleş et al. (2017) included observations beginning from 2005 and they tested the effect of sentiment on energy prices. Therefore, the second contribution of this thesis is to construct a new composite sentiment index for Borsa Istanbul using monthly data beginning from 1997 to 2017. Investor sentiment proxies' data used in the construction of the composite index include monthly observations on closed-end fund discount, mutual fund flows, turnover ratio, share of equity issues in aggregate issues, repo shares in mutual fund portfolios, and volatility premium.

Third, the CMAX crisis indicator will be used to detect the crisis periods in the period between 1997 and 2017, and the crisis periods detected will be separated as local and international based on their origin to analyze if the pattern of investor sentiment differs between locally and internationally originating crises. Moreover, the pre-crisis and post-crisis periods are also included in the analysis. It is expected that the effect of sentiment is high during the crisis periods, and it is hypothesized that there is a negative relationship between investor sentiment and future BIST 100 index returns. Moreover, since the whole period includes all the sample from no crisis, local and international crisis periods, the effect of investor sentiment will be combined in this period and it is expected to be higher. Therefore, it is hypothesized that the effect of investor sentiment is higher in the whole period relative to the crisis periods. Furthermore, during the local crisis since investors have alternatives to invest in other countries' markets, it is expected that the effect of investor sentiment would be higher. Hence, it is also hypothesized that the effect of investor sentiment is higher in the local crisis periods relative to the other periods. Thus, another contribution of the thesis is to test if the effect of investor sentiment on future returns varies based on the origin of the crisis.

Moreover, different from the existing studies, Carrion-i-Silvestre et al. (2009) unit root test is applied which considers the structural breaks, and macroeconomic factors such as change in the industrial production index, change in the consumer price index and change in exchange rate are included in the analysis as control variables to eliminate their possible effect on investor sentiment which constitutes the last contribution of this study.

Therefore, this thesis may shed light to the literature in terms of finding the probable effects of investor sentiment on stock returns during the crisis periods, which will give an insight about the irrational behavior of investors during these times in Borsa Istanbul. Moreover, it is believed that this study will have a significant contribution to investors, portfolio managers and policy makers by providing evidence on the effect of investor sentiment on the stock market, namely Borsa Istanbul, and its persistence during financial crises and whether this effect differs based on the origin of the crisis.

To realize the aim of the thesis, after the diagnostic tests and required corrections, the regression analysis will be conducted for the "whole period", "no crisis period", "all crisis periods", "local crisis period", and "international crisis period" respectively. Further, as a robustness check, an additional variable ($SENT_{t-1}$ * Crisis) will be added to the whole sample regression model as an interaction term. Finally, for the last step, to investigate the performance of the constructed sentiment index relative to the other proxies, the same regression equations will be tested by replacing the composite index with different investor sentiment proxies. The performance of each investor sentiment proxy with the constructed sentiment index in the regression analysis will be compared. Moreover, the relationship between investor sentiment and stock market return during the financial crises will also be examined for each proxy.

The thesis comprises four chapters. In the first chapter, investor sentiment will be defined from both psychological and financial points of view, and the rational and irrational investor sentiment will be explained. Then, the previous empirical literature of investor sentiment will be summarized. Lastly, the role of investor sentiment during the crisis periods will be discussed based on the related studies.

In the second chapter, first the direct and indirect proxies of sentiment will be explained, then the composite sentiment indices will be introduced, and comparison of the proxies will be presented based on empirical studies.

In the third chapter, the aim and the hypotheses of the study will be presented, the data and the sample will be described, and a composite sentiment index will be constructed using the principal component analysis (PCA).

In the last chapter, following the determination of the crisis periods, the methodology and the empirical findings will be presented. Moreover, in Chapter 4, robustness tests will be applied for the comparison of investor sentiment proxies with the constructed index and the relationship between investor sentiment and stock market return during the crisis periods will be investigated for each proxy.

CHAPTER ONE
INVESTOR SENTIMENT

Traditional finance theories about investors' decision-making process rest on the assumptions of rationality, risk-taking behaviors of investors and their predictions about the future. However, these assumptions are criticized by behavioral scientists that they do not reflect reality. In the real world, people do not always behave in a rational way while making investment decisions. In asset pricing models such as the Capital Asset Pricing Model (CAPM) and the Fama-French Factor Models, the expected returns are assumed to be determined by systematic (market) risk which is the combination of equity, interest rate, currency, commodity and liquidity risks (Gallati, 2003: 24), and they do not include any psychological factors as a source of risk in these models. However, emotions play a vital role in the behavioral asset pricing models (Kıyılar and Akkaya, 2016: 321). Accordingly, behavioral finance defends bounded rationality and argues that investors follow their emotions while making crucial investment decisions (Barberis and Thaler, 2003). With the rise of the behavioral finance theories, these emotions and psychological factors are considered as a source of systematic risk in finance by the behavioral scientists (Kıyılar and Akkaya, 2016: 315). As a result, sentiment which is defined as "an organized system of emotional dispositions centered about the idea of some object" (McDougall, 2001: 115) became a subject of interest in the financial markets research. Succinctly, investor sentiment refers to the optimism and pessimism level of investors about the market.

In this chapter, first psychological and financial meanings of sentiment will be defined and the differences between rational and irrational investor sentiment will be explained. Second, empirical literature on investor sentiment will be summarized in terms of the studies that investigated sentiment in the United States (U.S.), in the other developed markets, in emerging markets and in Turkey, respectively. Finally, the behavioral finance point of view to the financial crises and the role of investor sentiment during the crises periods will be discussed, and the related studies will be reviewed.

1.1. INVESTOR SENTIMENT

In this section, first the differences between emotions and sentiment will be clarified from the psychological point of view. Second, investor sentiment will be defined and the investor sentiment model of Shleifer (2000) will be explained. Finally, rational and irrational investor sentiment will be differentiated, and the related literature will be discussed.

1.1.1. Emotions and Sentiment

Philosophers such as David Hume, Adam Smith and Thomas Reid argued that for people themselves and for their social existence; emotions are crucial. According to these philosophers, without emotions none of the science could be complete (Evans, 2002: xi). In these years (two and a half centuries ago) emotions and sentiment referred exactly to the same thing. However, as stated by Heider (1958: 175) in 1920 Mr. Shand differentiated the concepts of "emotion" and "sentiment". Following Mr. Shand, McDougall (2001: 115) defined sentiment as "an organized system of emotional dispositions centered about the idea of some object". Beaglehole (2015: 19) explains this definition of sentiment as a complex disposition that combines various emotions to a single object or event, such as patriotism.

Basically, sentiment could be classified as positive and negative. Positive sentiment is associated with liking, and negative sentiment is associated with disliking of something such as a person or an impersonal entity (Heider, 1958: 174). Positive sentiments such as love, liking, affection and attachment are associated with attraction to an object, on the other hand negative sentiments such as hate, dislike and aversion are associated with avoidance of an object (McDougall, 2001: 116).

As discussed by Aronson, Wilson and Akert (2010: 223); emotions may sometimes act as heuristics while making decisions which is named as "How do I feel about it?" heuristic. By employing this heuristic, people may make rapid decisions based only on their emotions. The problem occurs when the source of this feeling is unknown. For example, people may feel great when they hear their favorite song in the radio, and because of that positive mood they may decide to buy something that they do not actually need by misattributing their feelings. Therefore, because of that heuristic, people might make wrong decisions. That is why this heuristic is widely used in marketing, that is while presenting their product; advertisers and retailers want to create good feelings with the purpose of selling their product more (Aronson, Wilson and Akert, 2010: 224).

1.1.2. Investor Sentiment

Sentiment analysis or opinion mining about the products or services is a technique widely applied in marketing research. It basically analyzes individual's opinions, sentiments, emotions and attitudes from written language such as blogs or social media tools (Liu, 2012: 1). Similarly, recently in financial research, the role of investor sentiment started to attract the attention of behavioral finance researchers.

Financial decisions contain risk and uncertainty, and for that reason emotions play a crucial role in financial decision making (Nofsinger, 2004: 86). It is argued that mood and emotions felt today affect investors' decision-making process. For example, sunny days affect people's mood positively and they feel happier relative to the rainy days, and these optimistic feelings may affect investment decisions, consecutively investors tend to buy stocks rather than sell during these days (Hirshleifer, 2001: 18; Nofsinger, 2004: 89). Constitutively, investor sentiment refers to the general feelings of optimism and pessimism levels of investors about the market. Investor sentiment is referred to as "animal spirits" by Keynes, and economists argued that it has an influence on the real economy (Ludvigson, 2004: 29).

In the financial markets, there are some investors who do not behave rationally and who follow noise rather than fundamentals or information at hand while making investment decisions. These kinds of investors are defined as "noise traders" by Black (1985). Efficient Market Hypothesis (EMH) assumes that the trades of irrational noise traders are random, so they could cancel each other. Moreover, EMH suggests that rational arbitrageurs in the market could eliminate irrational investors' influence on prices. Hence, irrational investors are assumed not to affect prices (Shleifer, 2000: 2). However, these arguments contradict with the arguments of behavioral finance researchers who suggest rational arbitrageurs who are assumed to eliminate irrational investors' influence on the market are limited, and behavioral finance argues that market outcomes and asset prices may deviate from equilibrium because of investor sentiment (Bodie, Kane and Marcus, 2010).

Moreover, according to the classical finance asset pricing models, such as the Capital Asset Pricing Model (CAPM) and Fama-French factor models, the only factor that determines the expected returns of the stocks is systematic (market) risk which is proxied by beta, market capitalization and book-to-market ratio, respectively (Statman, Fisher and Anginer, 2008: 20). As emphasized by Gallati (2003: 24) systematic (market) risk is composed of equity, interest rate, currency, commodity and liquidity risks, and classical finance theories disregard the effect of psychological factors. On the other hand, behavioral financiers regard investor sentiment as an additional source of systematic risk that has to be priced (Brown, 1999: 88; Kıyılar and Akkaya, 2016: 315; Statman, Fisher and Anginer, 2008: 20). The reason is that, since the changes in noise traders' sentiments are unpredictable, it is probable that these changes may affect stock prices (Verma, Baklacı and Soydemir, 2008: 1303). On this basis, investor sentiment is defined by Baker and Wurgler (2007: 1) as "a belief about future cash flows and investment risks that is not justified by the facts at hand". Similarly, Shefrin (2008: 216) also defined investor sentiment as "aggregate errors of investors being manifest in security prices".

Additionally, Shleifer (2000: 113) constructed an investor sentiment model with several heuristics (i.e. conservatism and representativeness) and biases (i.e. underreaction and overreaction) which are inconsistent with EMH to comprehend the way investors form their beliefs. Based on this model, when investors do not react to the earnings news about the company while revaluing the company's stocks, it means they demonstrate conservatism heuristic. This behavior, in turn, results in underreaction to the earnings announcements because investors tend to think that earnings will eventually revert to the mean (Shleifer, 2000: 113). Conservatism is defined by Montier (2003: 4) as "a tendency to cling tenaciously to a view or a forecast". In other words, people think that it is very hard to change from one situation to another. In earnings predictions investors consider that positive earnings will be followed by positive ones, and negative earnings will be followed by negative ones (Shefrin, 2002: 35). These considerations, eventually, result in underreaction to the earnings news.

On the other side, Shleifer (2000: 113) argued that investors employ representativeness heuristic when they receive earnings news repeatedly, and that behavior causes an overreaction to the news because investors believe that there is an earnings trend. Investors who are exposed to representativeness heuristic rely on similarities and stereotypes (Tversky and Kahneman, 1974: 1124). For example, historical prices of the stocks could be a representative for the future performance for investors. Therefore, investors associate good company stocks with higher returns, and poor company stocks with lower returns (Döm, 2003: 50). Consequently, representativeness heuristic leads to overreaction to the earnings news. Overreaction, in turn, leads to fast increases in prices, so the stocks will be overpriced, and as a result the returns will decrease (Shleifer, 2000: 113).

1.1.3. Rational versus Irrational Investor Sentiment

Some researchers asserted that investor sentiment has both rational and irrational components (Aydoğan and Vardar, 2015; Verma, Baklaci and Soydemir, 2008; Verma and Soydemir, 2006). They suggested that not all sentiment is due to noise, it may also be caused by fundamentals. Shleifer and Summers (1990: 23) argued that events such as public announcements of dividends may change the investors' demand for securities, their risk attitudes and trading behaviors. These kinds of demand changes could be regarded as rational. In this regard, Brown and Cliff (2004a: 417) expressed that if investors have bullish expectations about the market, this can be either a rational reflection or an irrational hope about the future expectations, or it can be the combination of both.

Following these explanations, Verma and Soydemir (2006) examined the spillover effect of U.S. individual and institutional investor sentiments to other markets. They found that the sentiment spread internationally from the U.S. stock market, and both rational and irrational factors influence individual and institutional sentiments. However, they found that the international effect of the U.S. stock market is mostly related with the fundamental (or rational) factors. In another study, Verma, Baklaci and Soydemir (2008) tested investor sentiment by separating it into two components as rational and irrational. They found that although irrational component of sentiment is effective on stock returns, the rational component's effect is much more.

According to these pioneer studies, a few researchers analyzed the rational and irrational components of sentiment in various stock markets. Calafiore (2010), initially, investigated the effect of Brazilian investor sentiment on the returns and volatility of the Bolsa de Valores de São Paulo, Brazilian stock market (Bovespa). In contrast to the findings of Verma, Baklaci and Soydemir (2008), he found that the effect of irrational investor sentiment is higher on stock returns in the Brazilian stock market. Secondly, Calafiore (2010) investigated the effect of U.S. investor sentiment on the returns and volatility of the Brazilian stock market index. In this case, Calafiore (2010: 74), found that the effect of rational sentiment is more pronounced, and there is no significant effect of U.S. irrational sentiment on Bovespa returns or volatility. This result is consistent with the findings of Verma and Soydemir (2006) who emphasized that the international effect of the U.S. stock market is mostly related with the fundamental (or rational) factors.

Moreover, Johnk and Soydemir (2015) separated investor sentiment into rational and irrational components while testing a conditional CAPM in Standard and Poor's 500 (S&P 500) sectors. They found that irrational investor sentiment has a significant role in the conditional CAPM which means when irrational sentiment raises, conditional volatility will also rise (Johnk and Soydemir, 2015: 118).

Furthermore, in Turkey a few researchers decomposed sentiment into its components as rational and irrational while examining the impact of sentiment on the Turkish stock exchange market. For instance, Bayram (2011) examined the relationship between stock returns and consumer/business sentiments in Borsa Istanbul by differentiating between rational and irrational components of sentiment. Consistent with the previous studies, Bayram (2011: 106) found that both rational and irrational factors of the consumer and business sentiments have an influence on stock market returns in Turkey. However, contrary to Verma, Baklaci and Soydemir

(2008), irrational component of the sentiment is not significant for Turkey. Similarly, Sayım and Rahman (2015) found that there is a positive relationship between investor sentiment and Borsa Istanbul (BIST) returns, and both rational and irrational components have an influence on returns. Moreover, they found that there is a negative relationship between rational investor sentiment and BIST volatility (Sayım and Rahman, 2015: 517). Therefore, when there is an unexpected change in rational investor sentiment, the volatility will decrease.

On the other hand, Aydoğan and Vardar (2015) examined the investor sentiment on industrial basis in Borsa Istanbul. Consequently, they found that only the Transportation and Telecommunication industry is affected from rational investor sentiment and the others are affected solely from irrational investor sentiment. Therefore, based on the above studies and their findings, it is apparent that investor sentiment could result from both rational and irrational future expectations of the investors in the financial markets.

1.2. PREVIOUS EMPIRICAL LITERATURE

Based on the noise trader approach of Black (1986) and DeLong, Shleifer, Summers and Waldmann (1990), many researchers became curious about the effect of noise traders, who are exposed to sentiment, on stock markets. However, the major difficulty researching investor sentiment is that it cannot be observed directly in the market, so it is very hard to measure it. Although in some countries there are some surveys such as American Association of Individual Investors (AAII) to measure it directly; they are not available in all countries. For that reason, researchers mostly used proxies, such as closed-end fund discounts, which are believed to represent investor sentiment. These proxies and their relationship with investor sentiment will be discussed in detail in Chapter 2. This chapter is devoted to the discussion of the studies on investor sentiment measured by variety of proxies in various markets and their findings.

Investor sentiment literature is mostly focused on the U.S. stock market. In this section, first, these studies that were conducted in the U.S. will be discussed. Secondly, the research that is performed in other developed markets and the studies that were conducted in a cross-country context will be reviewed. Lastly, the research on sentiment in the developing markets, including Turkey, will be explained in detail.

One of the pioneer studies on sentiment is done by Brown (1999) by examining the relationship between investor sentiment and closed-end fund volatility. He used a direct sentiment measure, namely American Association of Individual Investors (AAII) Sentiment Survey, which is published in the U.S. periodically. As a result of the analyses, Brown (1999) found that there is a strong relationship between closed-end fund volatility and investor sentiment, which suggests that irrational investors in the market have a great influence on asset prices and cause an increase in risk by generating additional volatility.

On the other hand, Otoo (1999) used the consumer confidence index (CCI) of Conference Board and the University of Michigan Consumer Sentiment Index to measure the effect of investor sentiment on stock prices. Based on the analyses, a strong and positive contemporaneous relationship is found between investor sentiment and stock prices.

Moreover, Fisher and Statman (2000) examined the effect of sentiment of different groups of investors on S&P 500 returns. They divided the investors into three groups as small (individual) investors, medium investors (newsletters writers) and large investors (Wall Street strategists). For the small investors AAII survey data, for the medium investors Investors Intelligence (II) survey data, and for the large investors Merrill Lynch survey data were used. Small and large investors' sentiments are found to be inversely related with the S&P 500 returns. However, although medium investors' sentiment is also negatively related with the returns, it is not statistically significant. In another study, Fisher and Statman (2003) measured investor sentiment with the CCI of Conference Board and the University of Michigan Consumer Sentiment Index. Similar with their previous research, they found a negative relationship between investor sentiment and future stock returns. However, when they examined the relationship between changes in investor sentiment and contemporaneous stock returns, similar with the study of Otoo (1999), they found a positive relationship, which means high stock returns leads to higher consumer confidence .

Furthermore, Lee, Jiang and Indro (2002) analyzed the effect of investor sentiment on volatility and excess returns of Dow Jones Industrial Average (DJIA), S&P 500 and National Association of Securities Dealers Automated Quotations (NASDAQ). As a sentiment indicator they used Investors' Intelligence of New Rochelle sentiment index, which is one of the direct indicators of investor sentiment. Consistent with previous research findings, they found a positive correlation between change in sentiment and contemporaneous excess returns. On the other hand, sentiment and market volatility is found to be negatively correlated (Lee, Jiang and Indro, 2002). Brown and Cliff (2004a) also used a direct survey measure of sentiment, and they found that when sentiment is high pointing to an increase in the optimism level, the stocks are overvalued, and this leads to low future returns as the price will revert to its intrinsic value. In their other paper, Brown and Cliff (2004b) constructed a composite sentiment index by using a number of proxies, and they found a bi-directional relationship between investor sentiment and stock returns. However, they indicated that the effect of market returns on sentiment is stronger than the effect of sentiment on market returns (Brown and Cliff, 2004b: 3).

As executed by Brown and Cliff (2004b), Baker and Wurgler (2006) also constructed a composite sentiment index and measured the stock return and sentiment relationship by forming different portfolios based on several firm characteristics. As a result of their analyses they reached some theoretically crucial results as when sentiment increases, stocks will be more preferable for optimists and speculators. Hence, younger, smaller, unprofitable, high volatility, non-dividend-paying and distressed stocks tend to earn relatively low future returns. Therefore, there is a negative relationship between investor sentiment and stock returns that possess these characteristics. Baker and Wurgler (2007) and Glushkov (2009) also showed that these kinds of stocks are affected by investor sentiment the most, in other words; they have relatively greater sentiment sensitivity. Moreover, Lemmon and Portniaguina (2006) used University of Michigan consumer confidence index and Conference Board consumer confidence surveys to measure investor sentiment, and they also found that sentiment forecasts the returns of small stocks. Therefore, from the studies that were conducted in the U.S. stock market, it could be concluded that there is an effect of investor sentiment on the market, and mostly smaller firms' stocks are influenced by sentiment.

There are also some other sentiment studies that were conducted in a cross-country context and they mostly focused on the European, Japanese, Canadian, and Australian markets and compared them within themselves or with the U.S.. Among others, Jansen and Nahuis (2003) examined the relationship between consumer confidence, as a measure of investor sentiment, and stock returns for 11 European countries namely Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain and the United Kingdom (U.K.). Based on their results, except Germany, they provided evidence of a positive relationship between consumer confidence and stock returns of the analyzed countries. On the other hand, Finter, Niessen-Ruenzi and Ruenzi (2012) discussed that there is only contemporaneous effect of investor sentiment, measured by composite sentiment index, on returns of the German stock market.

Furthermore, Schmeling (2009) used the consumer confidence index as a proxy for investor sentiment and analyzed its effect on stock returns of 14 European countries, Japan, Australia, New Zealand and the U.S., which are the most liquid markets in the world. Their results indicate that sentiment is a predictor of expected returns across countries. It is also found that sentiment is more pronounced for short and medium-term horizons.

In addition to the consumer confidence index, Bathia and Bredin (2013) also used equity fund flow, closed-end equity fund discount and equity put-call ratio to measure investor sentiment, and they examined the relationship between investor sentiment and G7 countries' stock market returns. Consistent with the previous studies, their results show that the effect of investor sentiment is mostly experienced in value stocks, and there is a negative relationship between investor sentiment and future stock returns.

Baker, Wurgler and Yuan (2012) also investigated the investor sentiment across countries. They constructed an investor sentiment index for Canada, France, Germany, Japan, the U.K. and the U.S.. Their results indicate that sentiment could predict the returns of high volatility stocks. Future returns of these stocks are inversely related with investor sentiment.

The effect of investor sentiment is a notable research issue also in the developing markets. For instance, Rehman (2013) examined the effect of investor sentiment in the Karachi stock market. According to the results, it is observed that the stock market returns are significantly affected from the investor sentiment in that market.

Similarly, Ni, Wang and Xue (2015) and Yang and Hasuike (2017) measured the effect of investor sentiment in the Chinese stock market. Ni, Wang and Xue (2015) used the turnover ratio as the sentiment proxy, while Yang and Hasuike (2017) constructed a composite sentiment index. Their results show that there is a significant effect of investor sentiment in the Chinese stock market. Finally, Hu, Huang, Chang and Li (2015) examined the effect of investor sentiment on individuals' trading behavior in Taiwan stock market. They used the option implied volatility index (VIX) and the ratio of the number of advancing issues to declining issues as a proxy of investor sentiment. Based on their results, the relationship between investor sentiment and trading frequency in one-minute intervals is positive. Their results show that there is evidence of positive feedback trading in the Taiwan stock market and investor sentiment plays a significant role.

Effect of investor sentiment on stock returns was also studied widely in Turkish stock market by using different proxies. Kandır (2006) examined the forecasting ability of investor sentiment, as measured by consumer confidence index, on BIST financial sector stock returns for the period 2002-2005. Based on the results, it is evident that most of the financial sector stock returns can be forecasted by the consumer confidence index. Moreover, Canbaş and Kandir (2007) used closed-end fund discounts, average fund flow of mutual funds, and the ratio of net stock purchases of foreign investors to BIST market capitalization as proxies for investor sentiment. They analyzed the effects of investor sentiment on BIST sectoral indices returns for the period 1997 to 2006. Based on their regression analysis, they found that investor sentiment systematically affects stock returns.

In another study, Canbaş and Kandir (2009) implemented a Vector Autoregressive (VAR) model and Granger causality tests for the period 1997 to 2005 using six proxies for investor sentiment, namely closed-end fund discounts, mutual fund flows, odd lot sales ratios, share of equity issues in aggregate issues, repo shares in mutual fund portfolios, and BIST turnover ratios. They also included two dummy variables as 1999 Marmara earthquake and 2001 financial crisis into their analyses. They found that there is an effect of stock portfolio returns on all investor sentiment proxies except share of equity issues in aggregate issues. However, the relationship is unidirectional, that investor sentiment has not forecasting power on future stock returns. In addition, the two dummy variables, 1999 Marmara earthquake and 2001 financial crisis, affect stock portfolio returns (Canbaş and Kandir, 2009).

Furthermore, Olgaç and Temizel (2008) used the consumer confidence index to analyze the effects of investor sentiment on BIST-30 index in long- and short-term horizons. For the long-term relationship co-integration test and for the short-term relationship VAR model were implemented on monthly data for the period 2004 and 2007. Based on the analysis, positive relationship was observed between CCI and BIST 30 index, and in this relationship, their evidence showed that BIST-30 index influences investor sentiment which supports the findings of Canbaş and Kandir (2009).

Likewise, Topuz (2011) investigated the causality relation between CCI and BIST 100 index for the period 2004 and 2009. The supportive results show that stock prices affect investor sentiment, so there is a unidirectional relationship between the two. Korkmaz and Çevik (2009) also examined the causality relation between investor sentiment and BIST 100 index return, but they used the Real Sector Confidence Index instead of CCI. They found that these two variables affect each other, so there is a bidirectional causality between the two.

On the other hand, Kale and Akkaya (2016) explored the effects of CCI and real sector confidence index on a sectoral basis in Borsa Istanbul (BIST). The selected sectoral indices include aggregate, financial, industrial, service and technological indices. They also included the Michigan University Sentiment Index, VIX volatility index and GFK Germany Consumer Climate Index into the model to observe the international effects of sentiment. The results are consistent with the previous research findings that unidirectional relation between stock returns and CCI (stock returns affect CCI), and bidirectional relationship between stock returns and real sector confidence index exist. Additionally, they found that there is an effect of Michigan University Consumer Sentiment Index and VIX volatility index on all stock indices of BIST. However, their results show that there is no effect of GFK Germany Consumer Climate Index, so they argued that Turkey is mostly affected from the U.S. confidence climate.

Further, Kaya (2017) investigated relationship between investor sentiment and stock returns by constructing an investor sentiment index, and annual data between 1997 and 2016 was used. The findings support unidirectional causality from investor sentiment to stock returns. Finally, Canöz (2018) also analyzed the causality relation between CCI and BIST 100 index using a different measurement method, namely Toda-Yamamoto Causality Test. The results are again consistent with the previous research that there is a unidirectional relationship from stock returns to the CCI.

Different from previous studies, Çelik (2013) examined the relationship between investor sentiment and sovereign risk in Turkey for the period from 2004 to 2010. JP Morgan EMBI+ spread was used for the sovereign risk, and CCI was used for the investor sentiment. Based on their results, although there is no long-run relationship between investor sentiment and sovereign risk, there is a short-run relationship between the two.

Moreover, Keleş, et al. (2017) investigated the short-run and long-run effects of energy prices on investor sentiment that is proxied by composite sentiment index. Based on their results, although there is a long-run relationship between sentiment index and energy prices, there is no evidence of short-run relationship between two.

Lastly, Uygur and Taş (2014) investigated the investor sentiment effect on conditional volatility of the various sectoral indices in BIST. The analysis results show that the effect of investor sentiment, which is measured by the trading volume, is mostly seen in the industry and banking indices.

Beside these studies, there are also limited number of dissertations investigating the relationship between investor sentiment and financial markets in Turkey. First, Beker (2006) analyzed the effect of investor sentiment on BIST by using closed-end fund discounts as a proxy for investor sentiment for the period January 1998 to September 2005. As a result of the analyses, evidence of investor sentiment's effect on the stock market was provided.

Second, Şenkesen (2009) analyzed the effect of investor sentiment on Turkish bond yields for the period from 2003 to 2008. As a sentiment indicator, CNBC-e Consumer Confidence Index, VIX volatility index and country risk premium were used. Şenkesen (2009) found that investor sentiment has a significant effect on bond yields in Turkey.

Third, Akdağ (2011) examined the relation between trading volume (as a proxy for sentiment) and stock returns for the period 2005 to 2010. In the study, investor sentiment in developed and developing countries were compared, and as a result, it is found that the effect of investor sentiment is significantly higher in developing and developed Asian stock markets.

Fourth, Uygur (2015) examined the impacts of investor sentiment on asset returns for stock market indices, individual stocks and economic sectors for the period from 1988 to 2006 for different stock market indices namely the U.S., the U.K., Germany, France, Japan, Hong Kong and Turkey. Across countries, it is found that there is asymmetric volatility and when sentiment is high, earnings shocks is found to be more influential on conditional volatility. In terms of individual stocks, it is found that when investor sentiment increases, conditional variance of the small and growth stocks increases also. Finally, as a result of the analyses on economic sectors, it is found that the effect of investor sentiment on conditional volatility is more powerful in industry, banking, and food and beverages sector indices in BIST.

Last, Korkmaz (2018) investigated the effect of investor and managerial sentiment on capital structure decisions of firms. She included the firms that are listed on BIST for the period between 2010 to 2017. Her results show that there is a negative relationship between variables which indicates the optimistic feelings of managers and investors lead firms to decrease their leverage levels and vice versa.

In sum, above mentioned empirical studies provide evidence that investor sentiment has an influence on the developed stock markets such as the U.S. as well as the developing stock markets such as Turkey.

1.3. INVESTOR SENTIMENT AND FINANCIAL CRISIS

As discussed by Brunnermeier and Oehmke (2013: 1222); in almost all financial crises there are two phases as a “run-up phase” and a “crisis phase”. While a run-up phase consists of bubbles and imbalances; in a crisis phase crisis erupts. Montier (2003: 77) indicated that there is higher possibility of bubbles to occur in markets where the number of inexperienced traders is high, the intrinsic value is uncertain, and buying on margin possibilities and difficulties in short selling exist. However, traditional finance theories become insufficient to explain the financial bubbles and crises at one point (Szyszka, 2011:121; Zouaoui, Nouyrigat and Beer, 2011:724). For example, in the crash of October 1987, the decline in the DJIA was around 22.6% which is too high to be explained by the economic variables (Zouaoui et al., 2011: 724). Moreover, as emphasized by Shefrin and Statman (2012: 103), since the bubbles indicate price deviations from fundamental values, they do not emerge in the rational markets.

Behavioral factors that cause financial bubbles are the existence of noise traders; and their tendency to show herd behavior, overconfidence, investor sentiment and overreaction which are interrelated with each other (Kıyılar and Akkaya, 2016: 230). Barberis (2013:16) categorized the theories that explain bubbles into two as preference-based and belief-based models. One theory in the preference-based model is related with the house money effect, that is, investors become less risk averse after their gains increase. Herewith, their demand to buy the assets goes up and in turn prices increase even further. Another theory of the preference-based model is about new technology, that is, investors tend to prefer stocks which are related with a new technology and overvalue these kinds of stocks (Barberis, 2013: 17).

On the other hand, there are three theories in the belief-based models. The first theory argues that when some investors are overly optimistic (bullish) about the asset, it will be overvalued. The second theory is about the representativeness heuristic which is introduced by Tversky and Kahneman (1974), and it argues that because of extrapolation of past outcomes of the asset, it will be overvalued. The last theory is based on the overconfidence of investors in their skills that they overestimate their own forecasts (Barberis, 2013: 16).

Furthermore, Kindleberger and Aliber (2005: 41) argue that one reason of the bubbles and crises is herd behavior. They indicate that economic expansions lead investors to become more optimistic, so their investment and consumption spending increase. Before profitable opportunities disappear, all investors want to benefit from them, so they follow the crowd. This behavior, in turn, leads to overvaluation of asset prices and create bubbles in the financial market (Kindleberger and Aliber, 2005: 42). Moreover, herd behavior eventually increases the market volatility and fragility in the market (Choe, Kho and Stulz, 1998; Bikhchandani and Sharma, 2000). One early example of the disappointing results of herd behavior is the tulip mania in the 17th century. Moreover, the overvaluation in Japanese stock and real estate markets in the 1980s, the media and telecom bubble in 2000, and global financial crisis in 2008 are the other examples that resulted from the herd behavior of investors (Bülbül, 2008: 70; Ede, 2007: 90).

In other words, these collective optimism and pessimism levels of investors may lead to economic crisis eventually. Over optimism levels of investors cause security prices to rise above their fundamental values creating bubbles. Shefrin and Statman (2012: 99) emphasized the Keynes' view that the optimism and pessimism levels of investors may be the behavioral reasons of economic booms and busts. Zouaoui et al. (2011: 741) stated that when investors are pessimistic, the future returns are relatively high, but in contrast when they are optimistic the future returns will be lower. The reason is that, the overvaluation (mispricing) of the market will eventually revert to the mean, and this leads to sharp decreases in stock prices, and thus crisis will occur.

There are limited number of studies that analyze the effect of investor sentiment on stock markets during the economic crisis periods. One of the pioneer studies was conducted by Baur, Quintero and Stevens (1998), and they analyzed the effect of investor sentiment on the stock market crash of 1987 by using the closed end funds discounts as an investor sentiment proxy. They found that, while stock prices were influenced by sentiment in 1987 stock market crash, there is no sentiment effect in the period surrounding the crash.

Furthermore, Zouaoui, et al. (2011) examined the effect of investor sentiment internationally for the crisis periods, and they separated the countries based on their market integrity and herd like overreaction. They used the consumer confidence index as a proxy for investor sentiment. They detected the crises periods with the CMAX crisis indicator that was recommended by Patel and Sarkar (1998). Based on their analyses, there is a significant effect of investor sentiment on stock markets during the financial crises; and this impact is more powerful in the countries that show herd-like behavior, overreaction and low institutional development.

In Turkey, Bolaman and Mandaci (2014) studied the relationship between stock market and investor sentiment for the crisis period. As a sentiment indicator, they used monthly CCI data and as a market indicator they used BIST 100 index data. Between the period 2003 and 2012, only 2008 crisis was detected, and at the crisis period structural breaks were identified. Augmented Dickey-Fuller (ADF) and co-integrations test results show that there is a long-term relationship between the variables. Therefore, Borsa Istanbul is under the effect of investor sentiment in the crisis periods.

Further, Ergün and Durukan (2017) investigated the effects of investor sentiment in the crisis periods between the years 1997-2017 on Borsa Istanbul. As a sentiment indicator, they used closed-end fund discounts, and similar with Bolaman and Mandaci (2014) they used the BIST 100 index returns as the market indicator. By using the CMAX methodology three crisis periods were detected as 1998 Asian crisis that is followed by the Russian crisis, 2001 Turkish financial crisis, and 2008 global financial crisis. They also differentiated these crisis periods as local and international. Based on their regression results it is found that there is a negative relationship between closed end fund discounts and market returns for the whole and local crisis periods. However, their findings showed no effect of investor sentiment on BIST 100 index returns for the no crisis, all crisis and global crisis periods (Ergün and Durukan, 2017: 315).

Lastly, different from previous studies, Çağlı, Ergün and Durukan (2018) examined the effect of investor sentiment in the presence of multiple structural breaks on BIST 100 index for the period between 1997-2017. First, they detected five structural breaks with Carrion-i-Silvestre et al. (2009) unit root test; second, they analyzed the cointegration between variables with Maki (2012) cointegration test; third, they investigated the long-run relationship between variables with dynamic ordinary least squares (OLS) method; and lastly, they examined the causality between variables with non-linear Granger causality. They used volatility premium as a sentiment proxy. Their results indicate that in the presence of structural breaks there is a long-run and positive relationship between variables, and the causality between BIST 100 index and volatility premium is bi-directional (Çağlı, Ergün and Durukan, 2018: 1094). Their findings that support a long-run relationship between value of BIST 100 index and investor sentiment is consistent with the findings of Bolaman and Mandaci (2014).

CHAPTER TWO
MEASURES OF INVESTOR SENTIMENT

Investor sentiment cannot be observed directly, and for that reason it is very hard to measure it. Besides the direct measurement methods such as surveys or questionnaires, many studies have attempted to determine the most accurate market-based proxy for investor sentiment. Studies that were conducted in this area used numerous proxies to measure the effect of investor sentiment on various stock markets; which were mentioned in the previous chapter.

The most commonly used direct proxies are American Association of Individual Investors (AAII) Sentiment Survey, Investors Intelligence (II) Index, UBS/Gallup Survey, Consumer Confidence Index (CCI), and Economic Sentiment Indicator (ESI). On the other hand, the most commonly used indirect proxies are closed-end fund discount, mutual funds (mutual fund flows and cash holdings of mutual fund portfolios), the share of equity issues in aggregate issues, ratio of odd-lot sales to purchases, trading volume, dividend and volatility premiums, initial public offerings (IPOs), option implied volatility index (VIX), and put-call ratio. Moreover, recently sentiment indices are started to be constructed by some researchers, such as Baker and Wurgler (2006), by using the combination of the aforementioned proxies using principal component analysis.

Besides these direct and indirect measures, internet search volume (ISV), such as Google trend analysis, is used to measure overall investor attention. Google trend analysis shows the search volume of a particular stock, and if investors search a name or ticker of a stock, it is obvious that they pay attention to it (Da, et al., 2011; Nawaz, 2014; Son-Turan, 2016). Investor attention is regarded as an indicator of investor sentiment; however, it is not possible to differentiate optimism and pessimism levels of investors with trend analysis. Hence, it is left out of the scope of the present study.

In this chapter, first each direct proxy will be explained. Second, each indirect proxy will be discussed. Third, the composite sentiment indices, particularly Baker and Wurgler (2006) sentiment index, will be clarified. Although there is no consensus about which sentiment proxy is more accurate and efficient; some studies compared these proxies with each other aiming to provide empirical evidence on their representative power of investor sentiment, and in the last section, these studies will be summarized.

2.1. DIRECT PROXIES

Direct measures of investor sentiment include surveys which are able to reflect the changes in the investors' psychology. The mostly used direct sentiment proxies are American Association of Individual Investors (AAII) Sentiment Survey, Investors Intelligence (II) Index, UBS/Gallup Survey, Consumer Confidence Index (CCI), and Economic Sentiment Indicator (ESI). In this section these surveys will be explained, respectively.

2.1.1. American Association of Individual Investors (AAII) Sentiment Survey

The American Association of Individual Investors (AAII) is a nonprofit organization which was established in 1978 by Dr. James B. Cloonan. The association's main purpose is to educate, inform and assist investors about financial instruments such as stocks, bonds and mutual funds. In July 1987, AAII started to measure investor sentiment of the individual investors by polling a random sample of its members. Each week, AAII Investor Sentiment Survey asks for the expectation of individual investors about the stock market for the next six months, and measure how bullish, bearish or neutral they feel. Around 100,000 members of the association answer the question of whether they feel bullish, neutral or bearish about the direction of the market over the next six months, and the percentage of their answers are published in the AAII Journal, and in other financial publications such as Barron's and Bloomberg (AAII Investor Sentiment Survey, 2018).

Based on previous literature (Brown and Cliff, 2004b; Calafiore, 2010; and Verma and Soydemir, 2006) a sentiment indicator by using AAII investor sentiment survey is constructed by taking the difference between the percentage of bullish investors (optimists) and the percentage of bearish investors (pessimists); and the spread between them is used as an investor sentiment proxy. Since the main target of AAII investor sentiment survey is individual investors, it is used as a proxy for individual investor sentiment by the analysts and researchers (Brown and Cliff, 2004b: 7; Calafiore, 2010: 59; and Verma and Soydemir, 2006: 131).

2.1.2. Investors Intelligence (II) Index

Investors Intelligence was established by AW Cohen in 1947 as an independent advisory firm on Wall Street (Investors Intelligence, 2018a). In its official website its mission is defined as "generating consistently valuable, clear, unambiguous and accurate investment research for clients, helping them make informed, and better, investment decisions" (Investors Intelligence, 2018b). For this purpose, they developed many technical analysis techniques such as the Advisors Sentiment Survey. Advisors Sentiment Survey has been initiated in 1963, and since this time it has been accepted as a contrarian indicator by majority of the financial media which referred to it as II Index (Investors Intelligence, 2018b).

Similar with AAII, II Index is published weekly as a bull and bear spread. The survey is constituted by reading and rating over a hundred independent market newsletters. The editors rank these newsletters as bullish, bearish and correction. As indicated by Lee, et al. (2002: 2282) when the advisory service predicts the market will go up or recommends purchasing stocks; the letters are labeled as bullish. On the other hand, when the predictions are in the opposite direction; the letters are labeled as bearish. According to the previous literature; since the newsletters are written by market professionals, the II index is used as a proxy for institutional investor sentiment (Brown and Cliff, 2004b: 7; Calafiore, 2010: 60; Verma and Soydemir, 2006: 131).

2.1.3. UBS/Gallup Survey

UBS/Gallup Sentiment Index has been published monthly in the Roper Center for Public Opinion Research; which is located at Cornell University that releases many other data from public opinion surveys. Initially, since its establishment in 1996, the index was started to be published quarterly, and then in 1999 it started to be published monthly by the joint attempt of UBS and Gallup Organization (UBS Index of Investor Optimism, 2018). At first, the survey was conducted as random interviews only for the U.S. investors who hold more than $10,000 in their wealth, and first two weeks of every month the organizations reached 1000 individual investors who satisfied this criterion (UBS Index of Investor Optimism, 2018). The results are published on the last Monday of the month. Beginning from 2002, the organizations extended their survey to the five biggest European countries, namely France, Germany, Italy, Spain and the United Kingdom. For each country, the survey is conducted monthly to 200 investors, and the results are published aggregately for the region in every month, and it is published separately for each country on a quarterly basis (UBS Index of Investor Optimism, 2018).

As summarized by Jacobe and Moore (2003), seven questions are asked to investors and they respond to each by ranking themselves as very or somewhat optimistic, very or somewhat pessimistic, or neither optimistic nor pessimistic. In the survey, there are two dimensions as personal and economic. In the personal dimension, participants are asked to state their feelings about their financial conditions, and in the economic dimensions they are asked to state their feelings about the overall economy such as economic growth, the unemployment rate, performance of the stock market and inflation. The answers are ranked on a scale between +2 to -2, and the sum of the two dimensions constitutes the overall score for the survey. The UBS/Gallup investor sentiment survey is assumed to be "representative and carefully sampled survey of investors" (Qui and Welch, 2006: 10).

2.1.4. Consumer Confidence Index (CCI)

Consumer Confidence Index (CCI) was started to be used as a proxy for investor sentiment by Fisher and Statman (2003). The main aim of their study was to find whether consumer confidence predicts the stock market. They found statistically significant and negative relationship between the level of consumer confidence and the following month’s stock returns for NASDAQ and small cap stocks. They also found statistically significant and positive relationship between changes in consumer confidence and changes in the sentiment of individual investors. They stated that since many consumers are also investors, consumer confidence index could be used as an indicator for investor sentiment which is supported by their analyses (Fisher and Statman, 2003: 121). In the U.S.; the University of Michigan Consumer Confidence Index and the Conference Board Consumer Confidence Index are the two measures that are released periodically, and they measure the public confidence about the overall economic indicators such as interest rates, unemployment and inflation (Fisher and Statman, 2003: 116).

George Katona conducted the first study about consumer confidence in 1946, and he designed a survey about consumer spending and expectations which was improved by University of Michigan, afterwards (Katona, 1968). The survey is conducted monthly by the Survey Research Center at the University of Michigan in the U.S.. Approximately, 500 interviews are conducted by telephone, and the participants answer 50 questions which focus on three main areas on how their prospects for their own financial situations are, how their prospects for the overall economy over the near term are, and how their prospects for the overall economy over the long term are. In other words, the survey focuses on personal finances, and business and buying conditions. University of Michigan has reported that the anticipation of consumers about the economic conditions such as interest rate changes and unemployment rate are generally close to actual rates (Surveys of Consumers, 2018). Therefore, it is a successful indicator that reflects the expectations about the overall economy.

On the other hand, Conference Board also releases the consumer confidence index monthly in the U.S.. As indicated in the Conference Board official website, the consumer confidence index is published since 1967 as a mail survey. It was conducted every two months until 1977, however since then it has started to be published on a monthly basis. It is conducted by Nielsen which is a global performance management company. The survey is composed of consumer confidence index, present situation index, and expectation index. The sample is selected randomly from the households, and the targeted size is approximately 3,000 (Consumer Confidence Survey Technical Note, 2011).

In Turkey, consumer confidence index (CCI) survey is conducted by the Central Bank of the Republic of Turkey (CBRT) in collaboration with the Turkish Statistical Institute (Turkstat). It is published monthly at the end of each month in the Turkstat website (Turkstat Consumer Confidence Index, 2018a). Between the period 2004-2012, the survey was conducted as a module to the “Household Labor Force Survey”; and after 2012 it has started to be conducted as part of “The Joint Harmonized European Union Programme of Business and Consumer Surveys” (Turkstat, 2018b). Similar with other countries, CCI in Turkey is calculated by the four sub-indices: households’ expectations about their own financial situation, overall economic conditions and unemployment rate over the next 12 months, and their saving probability over the next 12 months. As indicated in the Turkstat official website, the sample size is approximately 4,884 each month, participants are selected randomly, and a computer-based face-to-face interview is applied to each participant while conducting the survey. The index is rated between 0 and 200; the value above 100 indicates optimistic consumers, and the value below 100 indicates pessimistic consumers (Turkstat, 2018b).

2.1.5. Economic Sentiment Indicator (ESI)

Economics Sentiment Indicator (ESI) is a survey-based indicator of sentiment that is published monthly by the European Commission for each European Union member and candidate country. As it is emphasized in the European Commission website, ESI is a composite measure that is composed of five sectoral confidence indicators with different weights (European Commission ESI, 2018):

- Industrial confidence indicator (40 %),
- Construction confidence indicator (5 %),
- Services confidence indicator (30 %),
- Consumer confidence indicator (20 %),
- Retail trade confidence indicator (5 %).

Therefore, as indicated above, ESI provides insights about the beliefs of both demand and supply sides of the economy. When consumers and manufacturers are optimistic about the current and future economic situations, the ESI will increase (Gelper and Croux, 2010). In other words, there is a positive relationship between them. In Turkey, ESI has been published since January 2007.

2.2. INDIRECT PROXIES

The direct measures of investor sentiment have been criticized as they may be subject to methodological and response biases (Uygur, 2015: 16). For this reason, a substantial number of researchers used market-based proxies, and most of these proxies come from empirical puzzles such as IPO underpricing and closed-end fund discount (Uygur, 2015: 12). The most commonly used market-based proxies are; closed-end fund discount, mutual funds (mutual fund flows and cash holdings of mutual fund portfolios), the share of equity issues in aggregate issues, ratio of odd-lot sales to purchases, trading volume, dividend and volatility premiums, initial public offerings (IPOs), option implied volatility index (VIX), and put-call ratio. In this section, these indirect proxies of sentiment will be explained respectively.

2.2.1. Closed-End Fund Discount (CEFD)

Closed-end funds are investment companies that own well diversified investment portfolios which are managed professionally for income and profit (Dimson and Minio-Paluello, 2002: 1; Madlem and Sykes, 2000: 235). Closed-end funds are similar to the open-end funds that they both collect funds from individual investors and invest those funds in various securities. However, they differ from open end funds in a few aspects. First, closed-end funds can be bought only via brokers, but for open-end funds it is not necessary to use brokers; instead investors may send a check to a mutual fund company directly to obtain an open-end fund (Madlem and Sykes, 2000: 235). Second, the closed-end funds are issued only once with the fixed capitalization in the initial public offering, and they are traded in the secondary markets like as many securities in the market (Anderson and Born, 2002:

5). Therefore, supply and demand of the shares trading on the market determine its price (Dimson and Minio-Kozerski, 1999: 1). As indicated by Pontiff (1997: 155), the value of the fund's portfolio, which is called as net asset value (NAV), is computed based on the market prices of the underlying assets. Since they are traded in the secondary markets, their price may differ from their net asset value.

Most closed end funds are issued at prices lower than their net asset values, in other words they are issued at a discount, and these can be substantial and long-lasting (Anderson and Born, 2002: 12; Dimson and Minio-Paluella, 2002: 1). The closed-end fund discount is defined as the "average difference between the NAV of closed-end fund shares and their market prices" (Baker and Wurgler, 2006: 1655), and it shows a mean-reverting pattern in which share price increases eventually and discounts disappear (Dimson and Minio-Paluella, 2002: 1). As indicated by Madlem and Sykes (2000: 236), closed-end funds are issued with an approximately 12 percent discount to their NAV which creates a puzzle to solve, and since 1990s many researchers tried to explain the rationale behind this discount puzzle (Anderson and Born, 2002: 12). The closed-end fund discount contradicts with the assumptions of efficient market hypothesis, because the theory argues that investors always behave rationally, and stocks are correctly priced, so the closed-end fund prices should be equal to the NAV of the closed-end fund. Therefore, the discounts on closed-end funds create violations to the standard asset pricing models (Dimson and Minio-Paluello, 2002: 1; Madlem and Sykes, 2000: 238; Pontiff, 1997: 155).

As discussed by Lee, Shleifer and Thaler (1990:154-155) the puzzle of closed-end fund discounts comprises four parts: (1) even though the new funds are issued at a premium and then convert to a discount rapidly, it is unknown why investors still prefer to buy these funds, (2) the funds traded at a discount and it is unknown why the value is not equal to the NAV, (3) it is unknown why the discounts vary over time and across funds, and (4) it is unknown why the values are converted to the NAV during the termination of the closed-end funds. Initially, the puzzle has been tried to be explained within the scope of standard finance theories. The widely used explanations in this regard is the miscalculation of NAV and the misbehavior of the fund managers (Lee, Shleifer and Thaler, 1990: 156). Dimson and Minio-Paluello (2002: 10) discussed that the biases could occur while calculating

NAV although the market is efficient, or another explanation leans on the agency costs that may be reflected in the price of the funds.

However, none of these explanations are sufficient to solve the puzzle, and for that reason behavioral hypotheses are also developed to clarify the puzzle based on the theories such as market inefficiency and investor sentiment (Anderson and Born, 2002: 13; Malkiel, 1977: 857). As discussed for the first time by Zweig (1973), the expectations of individual investors may be reflected in the discounts of funds. Further, Lee, Shleifer and Thaler (1990: 161-162) explained that when noise traders are overly optimistic about the overall market, they tend to buy overpriced funds, and the price will decrease below NAV after they become pessimistic. Rational arbitrageurs do not prefer to buy the funds, because they are exposed to irrational noise trader risk that they may become more pessimistic and may force prices to further underperform. Since rational investors are risk averse, this risk should be priced at the market, and the way of pricing this risk in the closed-end funds could be realized by the discounts (Anderson and Born, 2002: 15).

Consequently, closed-end fund discounts are argued to reflect individual investor sentiment in the market, and the prior studies suggested that the discount is inversely related with investor sentiment (Baker and Wurgler, 2006: 1655; Brown, 1999: 83). Lee, Shleifer and Thaler (1991) argued that when investors are more pessimistic (negative sentiment) about future returns, closed-end fund discounts will be higher; and when investors are more optimistic (positive sentiment), it will be lower. In other words, when investors feel more optimistic, the closed-end fund discounts will be smaller (Halkos, 2005).

2.2.2. Mutual Funds

Mutual funds are the open-end investment companies that make investments by pooling money from individual and institutional investors and buy stocks, bonds or money market securities on behalf of these investors (Bodie, Kane and Marcus, 2010: 87). Mutual funds allow investors to invest in a variety of companies including large and expensive companies, and investors benefit from offerings of mutual funds such as liquidity, lower risk, ease of record keeping and diversification (Madlem and

Sykes, 2000: 2). Although investing in mutual funds is similar to investing in any stock, it differs in few respects. First, mutual fund investors do not obtain voting rights of the companies, and second, mutual fund investors do not own the shares of only one company, they own the shares of other companies that mutual fund managers invested in (Madlem and Sykes, 2000: 4).

Mutual funds can be categorized based on their investment policies such as money market funds or equity funds. They can also be categorized based on their income and growth such as fixed-income funds or index funds (Bodie, Kane and Marcus, 2010: 91). Since mutual funds contain various securities, the value of the fund changes depending on the value of each security that it holds. The share prices of the mutual funds are called as net asset value (NAV), and the mutual fund investors gain (lose) depending on the increase (decrease) in NAV plus income distributions namely, dividends and distributions of capital gains (Bodie, Kane and Marcus, 2010: 92).

Investors of mutual funds delegate their rights to manage their investments to the fund managers, hence their investments are managed by the professionals (Indro, 2004: 105). Therefore, individual investors, who are small and least informed, prefer to invest in mutual funds instead of investing in individual stocks (Bailey, Kumar and Ng, 2011: 2). It is considered that informed investors will directly invest in the stock market themselves, therefore since mutual fund investors are uninformed the flows to the mutual funds are thought to reflect individual investor sentiment. The researchers such as Warther (1995) and Bailey, Kumar and Ng (2011) documented that there is a positive relationship between mutual fund flows and future stock returns. In other words, when there is an inflow to the fund, future returns will be lower, and when there is an outflow to the fund the future returns will be higher (Bailey, Kumar and Ng, 2011: 2). It is also documented that mutual fund flows are a positive indicator of investor sentiment. When noise traders are optimistic (higher sentiment) about the market they will increase their holdings, and conversely when they are more pessimistic (lower sentiment) they will decrease their holdings (Lee, et al., 2002).

Moreover, mutual funds hold cash or cash equivalents in their portfolios. With these cash holdings, the managers of funds may fulfill the shareholders' redemption needs, they may pay the expenses (i.e. management fees) and distribute dividends, and they may use it for market timing (when the managers' expectation about stock market returns are low) (Yan, 2006: 67). Therefore, it is essential to hold a specific amount of cash for mutual fund portfolio managers. The mutual fund cash levels are also thought to reflect investor sentiment, however since the cash levels are determined by the managers of mutual funds; different from the mutual fund flows, the proportion of mutual fund assets held as cash is considered as an institutional investor sentiment (Brown and Cliff, 2004b: 12). It is argued that cash levels in mutual fund portfolios is negatively related to investor sentiment. In other words, when the portfolio managers are more optimistic (higher sentiment), cash holdings of the funds will be lower, because the managers expect the mutual fund investments will increase (Brown and Cliff, 2004b: 14). Holding relatively little cash may also be an indicator for the managers' overconfidence about the future returns (Simutin, 2013: 1457).

2.2.3. The Share of Equity Issues in Aggregate Issues

Loughran and Ritter (1995: 23) observed that the companies which issue equity either by initial public offerings (IPOs) or seasoned equity offerings (SEOs), are undervalued relative to the non-issuing companies in the subsequent five years. Even though the beta of the issuing firms is higher than the non-issuing ones, their returns are not higher, which contradicts with the expectations of the classical finance theories, and this situation creates a puzzle which is called as "new issues puzzle" (Loughran and Ritter, 1995: 24). Generally, the issuing firms have positive excess returns during the periods before the issuance, and they have negative excess returns during the periods after the issuance announcements (Cornett, Mehran and Tehranian, 1998: 2139).

The puzzle can be associated with the market timing of managers: before the issuance of shares, the firm is overvalued and hence managers desire to benefit from this overvaluation by issuing additional shares. These additional shares draw back the overvalued prices, and this leads to lower future returns (Baker and Wurgler, 2000: 2219; Cornett, Mehran and Tehranian, 1998: 2156). Since equity shares are able to predict future negative returns, it contradicts with market efficiency. Further, it is argued that the stocks may be overvalued as a result of investors' excessive optimism about the market. Therefore, in sum, when investors are overly optimistic (high sentiment) about the market, the share prices will be overvalued, and the managers wish to benefit from this overvaluation by issuing additional shares (Stambaugh, Yu and Yuan, 2012: 301). Consequently, the share of equity issues in aggregate issues (equity and debt issues) can be used as a positive indicator of investor sentiment (Baker and Wurgler, 2006: 1656).

2.2.4. Ratio of Odd-Lot Sales to Purchases

In stock markets, shares are generally traded with lots, and each lot contains 100 shares of stock. Investors who wish to trade in less than a lot are exposed to higher commissions, and these transactions are called as odd-lot transactions (Bodie, Kane and Marcus, 2005: 47). The odd-lot traders are believed to be uninformed individuals (Johnson, 2014: 669). According to the odd-lot theory, if investors follow the trades of these uninformed investors and if they make investments opposite to them, they may easily outperform the market (O'Hara, Yao and Ye, 2012: 9). The theory states that, uniformed odd-lot traders tend to increase their investments when the prices are near their maximum value, and they tend to decrease their investments when the prices are near their minimum value (Kewley and Stevenson, 1967: 103).

Therefore, it is argued that during the bull markets odd-lot purchases significantly increase, and in contrast, during the bear markets odd-lot purchases significantly decrease (Dyl and Maberly, 1992: 600). Since uninformed investors are associated with noise traders, ratio of odd-lot sales to purchases is believed to measure individual investor sentiment in a positive way, and when the ratio increases investor sentiment will also increase pointing to more optimistic investors (Brown and Cliff, 2004b: 11).

2.2.5. Trading Volume

Trading volume indicates the transaction amount of the shares in the stock market. It is discussed that overall trading volume in the world markets are too high to be explained by the classical finance theories that assume rationality (Odean, 1999; Glaser and Weber, 2007). Instead, as indicated by Glaser and Weber (2007: 2), the high amount of trading volume is tried to be explained with the "differences of opinion" and "overconfidence". The investors' prior beliefs or the way they interpret public information may differ, so differences of opinion can arise (Glaser and Weber, 2007: 2). On the other hand, the overconfidence arises when investors overestimate their information or beliefs, and in turn they tend to trade more. Since the overconfident investors overestimate the expected profits, they trade even when their profits are insufficient to account for their costs, and for that reason, afterwards their losses increase (Odean, 1999: 1280).

Similar to the overconfidence hypothesis, Baker and Stein (2004) argue that trading volume, or liquidity, may be an indicator of investor sentiment in the market. Irrational investors in the market generate sentiment shocks when they show overreaction to the private signals about expectations. When irrational investors (or noise traders) are overly optimistic (high sentiment), the market will be overvalued, and hence these investors' valuations are more than those of rational investors. Therefore, the overvaluation will result in overreaction and they will trade more, and the trading volume will increase which makes the market more liquid (Baker and Stein, 2004: 273). Akdağ (2011: 1) emphasized that equities with higher liquidity tend to earn lower expected returns, and conversely lower liquidity equites tend to earn higher expected returns. Based on these explanations, turnover ratio is thought to reflect investor sentiment which is calculated by dividing the trading volume of the stock market by its market value, and it is another positive indicator of investor sentiment that is used in the literature (Baker and Wurgler, 2007: 137).

2.2.6. Dividend and Volatility Premiums

Many researchers have discussed how companies should distribute their capital gains to the shareholders, whether they should distribute dividends or offer stock repurchases, and this created the dividend puzzle. Miller and Modigliani (1961) proposed the "dividend irrelevance theory", and they argued that rational investors do not have preference between dividends and stock repurchases. On the other hand, Lintner (1962) and Gordon (1963) defended the "bird in the hand" theory, and they asserted that when dividends increase, the risk of the stock will decrease so investors will prefer dividends instead of stock repurchases. Moreover, according to the "signaling theory", high dividends may be a signal for high future earnings (Miller and Rock, 1985). The common assumption of these theories is that the investors are rational. Baker and Wurgler (2004) relaxed this assumption by considering the existence of irrationality in the market, and they introduced the "catering theory" of dividends. They argued that paying dividends is related to the dividend premium in stock prices, and dividend premium is defined as "the difference between the average market-to-book ratio of dividend payers and nonpayers" (Baker and Wurgler, 2004: 1126).

Since dividend premium is related with the share price, managers cater investor demands to maximize the current price of their shares. For that reason, Baker and Wurgler (2004) investigated the source of investor demands, and they argued that one possible driver of dividend premium could be investor sentiment. They explained that dividend paying companies are perceived as less risky than nonpaying companies. Therefore, when the premium is high, investors will prefer safety, in other words, dividend paying companies; in contrast when the premium is low nonpayers will be preferable (Baker and Wurgler, 2004: 1126). They also emphasized that dividend premium and investor sentiment are inversely related. When investors are pessimistic, they will favor safer stocks which means dividend paying stocks; and conversely when their sentiment is optimistic, they will prefer nonpaying ones (Baker and Wurgler, 2004: 1132).

Moreover, as indicated by Baker, Wurgler and Yuan (2012) volatility premium could be used instead of dividend premium as a sentiment measure.

Moreover, volatility premium and dividend premium are strongly and inversely correlated with each other, and hence they can be substitutes of each other (Baker, Wurgler and Yuan, 2012: 274). The logic behind volatility premium is very similar to the dividend premium, that sentiment is more effective for the stocks which are hard to value and arbitrage, in other words for the stocks which are more volatile (Baker and Wurgler, 2006: 1646).

The volatility premium is defined as "the log of the ratio of the value-weighted average market-to-book ratio of high volatility stocks to that of low volatility stocks (Baker, Wurgler and Yuan, 2012: 274). When sentiment is low (more pessimistic investors), investors favor less risky stocks, so high-volatile or non-dividend paying stocks are undervalued, and the premium between high and low volatile stocks shrinks. In contrast, when investors are more optimistic about the market, investors prefer more volatile stocks, so they are relatively overvalued, and the premium goes up (Baker and Wurgler, 2006). Therefore, it is a positive indicator of investor sentiment.

2.2.7. Initial Public Offerings (IPOs)

Initial public offerings (IPOs) are widely discussed to be underpriced on the first day of their issuance, so they have abnormal initial returns and they underperform in the long-run, and many researchers tried to clarify these phenomena in their studies. For example, Ibbotson (1975: 264) argued that IPOs are underpriced to "leave good taste in investors' mouth", so the future IPOs from the same company may be sold at higher prices. In other words, underpricing is a signal about the quality of the issuing company (Allen and Faulhaber, 1989; Grinblatt and Hwang, 1989). Further, Rock (1986) developed a model for the underpricing of IPOs by incorporating asymmetric information and rationing. He stated that if the new shares are priced at the expected value, the uninformed investors will be eliminated in the market and give place to privileged investors when good issues are offered (Rock, 1986: 187). On the other hand, Loughran and Ritter (2002) explained why issuers are not upset about leaving money on the table. They emphasized that for the issuers the most important thing is the change in their wealth rather than the level of wealth.

Accordingly, they theorized that issuers will evaluate net growth in their wealth by summing the wealth loss that comes from leaving money on the table and the wealth gain that comes from retained shares from a price increase (Loughran and Ritter, 2002: 414).

Besides short-run underpricing of IPOs, Ritter (1991) also presented another anomaly about IPOs that they are overpriced, and they underperform in the long-run. Similarly, Loughran and Ritter (1995) also showed that issuing companies stocks significantly underperform relative to non-issuing firms stocks for five years after the offering date. Ritter (1991) explained this situation with the risk mismeasurement, bad luck, and fads and over-optimism. Therefore, there is a possibility that the anomalies of IPOs may result from investor sentiment.

Lee, Shleifer and Vishny (1991: 105) argued that when investors are more optimistic, the IPO activities should increase, and the stock prices will be higher than their fundamental values. In other words, individual investor sentiment affects the timing of IPO offerings. Further, IPO volume has a strong correlation with the closed-end fund discounts (Lee, Shleifer and Vishny, 1991: 106). Based on this evidence, Ritter (1991: 4) discussed that when investors are overly optimistic about the prospects of young growth companies, firms tend to go public to benefit from these "windows of opportunity". Therefore, the investor sentiment may be the reason of the long-run IPO underperformance.

Moreover, short-term IPO underpricing can also be explained by the investor sentiment. Ljungqvist, Nanda and Singh (2006: 1669) proposed a model that links IPO anomalies with the existence of "irrationally exuberant" investors in the market. They argued that when there is a possibility of increase in the sentiment demand, issuers underprice their IPOs to compensate the expected losses of their institutional (or regular) investors (Ljungqvist, Nanda and Singh, 2006: 1669). Therefore, from these studies, it can be stated that IPO market is sensitive to sentiment, and high first day returns on IPOs and number of IPOs are associated with investor optimism (Baker and Wurgler, 2006: 1656).

2.2.8. Option Implied Volatility Index (VIX)

VIX volatility index is a widely accepted market sentiment indicator and it is also referred to as market's "fear gauge" (CBOE VIX White Paper, 2018). As indicated in the Chicago Board Options Exchange (CBOE) website, VIX index simply measures the stock market implied volatility by reflecting the investors' expectations about future (30-day) stock market volatility. When the investors' expected volatility about the market increases, the investors' expected returns also increase and consequently the stock prices decrease. Investors react to this price decline by increasing their demand to the options market. The level of VIX index is affected from this demand fluctuations to the options market, and when demand increases VIX index also increases (CBOE VIX White Paper, 2018).

Therefore, there is a negative relationship between investor sentiment and VIX index. When investors are pessimistic, the demand to the options market increases and VIX index also increases; when they are optimistic the demand decreases and VIX index also decreases (Bandopadhyaya and Jones, 2008).

2.2.9. Put-Call Ratio

Similar with VIX index, put-call ratio is another derivative measure of investor sentiment. The put-call ratio shows the number of put options traded in S&P divided by the number of call options, where call options allow investors to buy commodities at a reduced price and put options allow investors to sell commodities at a stated price (Weir, 2006: 114). Identical with VIX index, the ratio is published periodically in the Chicago Board of Options Exchange (CBOE) website. The put-call ratio is believed to reflect sentiment, and it is widely used as a sentiment index by researchers and practitioners (Dennis and Mayhew, 2002: 479). When it is compared with VIX index, put-call ratio is believed to be a better measure of traders' activity and market sentiment, because different from VIX index, it is possible to break down the trading activities of investors as puts and calls with the put-call ratio, but VIX index just shows the magnitude of the fear of investors (Bandopadhyaya and Jones, 2008: 33; Weir, 2006: 115).

When the buyers of put options increase, it is considered that pessimism increases; and conversely when the buyers of call options increase, it is considered that optimism increases. Therefore, as emphasized by Bandopadhyaya and Jones (2008: 28), put-call ratio is also a ratio of pessimism to optimism. Since in general buyers of call is higher than the put options, as stated by Bandopadhyaya and Jones (2008: 29) the neutral value of put-call ratio is considered approximately 0.80. Therefore, when the ratio decreases below 0.70, the markets are considered strong, because optimism is more influential than pessimism during these times. In contrast, when the value increase above 1.1, the markets are considered weak, because this time pessimism is more influential in the market (Bandopadhyaya and Jones, 2008: 29). Hence, overall put-call ratio is a bearish, or negative, indicator of investor sentiment (Brown and Cliff, 2004b: 11).

2.3. INVESTOR SENTIMENT INDEX

Besides using one of the direct or indirect proxies, some researchers combined several proxies and tried to form a single composite investor sentiment index. Initially, Brown and Cliff (2004a) determined three measures of investor sentiment, namely advance-decline ratio, short interest, and closed-end fund discounts, and they used Kalman filter and principal component analysis (PCA) to form a composite sentiment index. After forming an index, they compared it with the survey data (Investors Intelligence Index) and found that both indices have a strong correlation with the market returns. Although the idea behind forming a composite index was initiated by Brown and Cliff (2004a), it gained importance and popularity especially with the study of Baker and Wurgler (2006), and afterwards their methodology was widely accepted and used by many researchers.

Baker and Wurgler (2006) stated that there are no perfect proxies for investor sentiment, therefore forming an index may help to reflect investor sentiment better. With this purpose, they determined six annual indirect proxies of investor sentiment as closed-end fund discount, turnover ratio, the number and average first day returns on IPOs, the equity share in aggregate issues, and the dividend premium. Before using the index in their further analyses, they also orthogonalized these proxies to macroeconomic variables for the purpose of eliminating the systematic risk. Last, they constituted a composite sentiment index based on first principal components of the proxies.

Following Baker and Wurgler (2006) methodology, several studies constructed investor sentiment indices by combining various proxies based on their own country specific data. For example, Glushkov (2009) combined eight direct and indirect monthly proxies to form a sentiment index in the U.S.. The proxies include investors intelligence sentiment index, dividend premium, closed-end fund discount, number and first day returns of IPOs, level and percentage change in margin borrowing, and the ratio of specialists' short sales to total short sales.

Similarly, Finter, Niessen-Ruenzi and Ruenzi (2012) constructed a German sentiment index by combining consumer confidence index, mutual fund flows, put-call ratio, trading volume, number and the returns of IPOs, and share of equity issues in new issues. Distinctively, they tested the validity of their composite index by correlating it with the stock returns which have high sensitivity of sentiment (i.e. hard to arbitrage stocks), and they found that there is a high correlation between them. Further, they found that sentiment index increases together with the tech bubble and decreases afterwards, and hence they argued that the composite sentiment index is a valid sentiment indicator (Finter, Ruenzi and Ruenzi, 2010).

On the other hand, Baker, Wurgler and Yuan (2011) constructed investor sentiment indices separately for stock markets of Canada, France, Germany, Japan, the UK, and the US, respectively. They considered annual data of volatility premium, number and initial returns of IPOs and market turnover which were selected based on the data availability of countries.

Rehman (2013) formed an investor sentiment index in the Karachi stock exchange by including six proxies: number and initial returns of IPOs, closed-end fund discount, dividend premium, share of equity issues in aggregate issues, and turnover ratio. Yang and Hasuike (2017) also improved the investor sentiment index with the proxies that are suitable for the Chinese stock market. They included closed-end fund discount, the number of new accounts opened, turnover rate and margin debt in their composite sentiment index.

Recently in Turkey, two studies formed an investor sentiment index. The first study was conducted by Keleş, et al. (2017), and they formed an investor sentiment index by including six proxies: consumer confidence index, share of equity issues in aggregate issues, number and initial returns of IPOs, mutual fund flows, and trading volume. Their composite sentiment index is composed of monthly observations from 2005 to 2016. The second study was conducted by Kaya (2017), and similarly her sentiment index is composed of six proxies: trading volume, closed-end fund discounts, number and first day returns of IPOs, share of equity issues in aggregate issues, and VIX volatility index. Different from the sentiment index of Keleş, et al. (2017) her sentiment index includes yearly observations from 1997 to 2016.

2.4. COMPARISON OF INVESTOR SENTIMENT PROXIES

Although there is no consensus about which sentiment proxy is a more accurate measure that reflects investor sentiment, few studies compared selected proxies to determine their prediction power. Neal and Wheatley (1998) compared three popular proxies in terms of their power to predict returns. The included proxies are the closed-end fund discounts, the ratio of odd-lot sales to purchases and the mutual fund redemptions. Their findings indicate that closed-end fund discounts are positively related with expected returns of small firms, but there is no correlation between discounts and expected returns of large firms. The positive correlation between mutual fund redemptions and expected returns of small firms is weaker, and there is also weak but negative correlation between fund redemptions and expected returns of large firms which indicates that the size premium can be predicted with mutual fund redemption. In contrast, the prediction power of ratio of odd-lot sales to purchases is very small (Neal and Wheatley, 1998).

On the other hand, Indro (2004) investigated the relationship between mutual fund flows and investor sentiment by comparing American Association of Individual Investors and Investor Intelligence weekly survey data with the mutual fund flows. Based on the results, it is found that mutual fund flows are strongly correlated with the sentiment level of newsletter writers and individual investors. This indicates that when investors are more bullish (higher sentiment) their investments into the mutual funds are higher. Similarly, when investments into the mutual funds are higher, newsletter writers become more bullish or more optimistic. Therefore, Indro (2004) demonstrated that mutual fund investors are affected from both economic fundamentals and investor sentiment.

Similarly, Qui and Welch (2006) compared the consumer confidence index and closed-end fund discounts with the UBS/Gallup survey data, respectively. Their findings indicate that although there is no correlation between closed-end fund discounts and UBS/Gallup survey, there is a strong correlation between consumer confidence index and the survey data. Thus, consumer confidence index is a better measurement of investor sentiment than the closed-end fund discounts (Qui and Welch, 2006).

Furthermore, Kandır, Çerçi and Uzkaralar (2013) examined the relationship between closed-end fund discounts and consumer confidence index. As a result of their analyses, long-run relationship was found between these two variables. The relationship between closed-end fund discounts and consumer confidence index is strong, significant and inverse. Therefore, they stated that both proxies of investor sentiment could be used interchangeably to measure investor sentiment in the market (Kandır, Çerçi and Uzkaralar, 2013).

Different from other studies, Chan, Durand, Khuu and Smales (2017) compared text-based sentiment proxy with the Baker and Wurgler (2006) sentiment index. Their results found no correlation between the two. Hence, they concluded that one or both of these proxies are not a valid measurement of investor sentiment (Chan, et al., 2017).

Overall, in sum, there is no consensus on which proxy reflects investor sentiment most accurately, and still it is an unsolved phenomenon in the investor sentiment literature.

CHAPTER THREE
INVESTOR SENTIMENT INDEX

As explained in the previous chapter there are various types of proxies to measure investor sentiment. Finding the most accurate proxy is not only difficult but also its accuracy varies based on the structure of the selected country's stock market. To deal with this problem; Baker and Wurgler (2006) constructed a sentiment index by combining various proxies for investor sentiment by taking their first principal component. Their index is composed of the closed-end fund discount, turnover ratio, number of IPOs, average first day returns of IPOs, share of equity issues in total equity and debt issues and dividend premium as proxies for investor sentiment. By following Baker and Wurgler (2006), one of the aims of this study is to form a sentiment index that is applicable to Turkey. After scrutinizing the related literature and considering the data availability; six proxies were selected. These are; closed-end fund discount, mutual fund flows, turnover ratio, share of equity issues in aggregate issues, repo shares in mutual fund portfolios, and volatility premium. The monthly data used covers the period between 1997 to 2017.

In the following parts, first the aim and hypotheses of the thesis will be clarified. In the second part, data and the sample will be described. In the third part, the method of principal component analysis (PCA) used to form a composite sentiment index will be explained. In the last part, PCA empirical results will be covered.

3.1. AIM AND HYPOTHESES

Based on the analysis of the literature presented in Chapter 1, a gap about the effect of investor sentiment on stock markets for the crisis periods is determined. The existing studies are limited. For that reason, the main aim of this study is to analyze the impact of investor sentiment on Borsa Istanbul as a developing market during the crisis periods beginning from 1997 to 2017.

However, before investigating the probable effects of investor sentiment on stock returns, it is crucial to select the appropriate investor sentiment proxy for Borsa

Istanbul. As indicated in Chapter 2 there are many proxies, indirect and direct, for investor sentiment, but none of these can reflect investor sentiment accurately. Instead of using those proxies separately, using a composite sentiment index may give more accurate results. Some studies, such as Baker and Wurgler (2006), constructed a sentiment index by considering several proxies. However, this index is not applicable to Borsa Istanbul since the data of the proxies included in the Baker and Wurgler's (2006) index are not all available. Additionally, there may be some other sentiment proxies that might be more suitable for the Turkish stock market. Thus, in Turkey, Kaya (2017) and Keleş, et al. (2017) constructed a sentiment index, but Kaya (2017) used annual data, and Keleş et al. (2017) included observations beginning from 2005 and they tested the effect of sentiment with their constructed index on energy prices. Therefore, in this thesis beginning from 1997 by using monthly data, first, a composite sentiment index for Borsa Istanbul is constructed as explained in this chapter.

Second, in Chapter 4, the CMAX crisis indicator is used to detect the crisis periods between January 1997 and November 2017, and the three periods detected are labeled as local and international based on their origin to analyze if the pattern of investor sentiment differs between locally and internationally originating crises. Moreover, the pre-crisis and post-crisis periods are also included in the analysis.

Shefrin and Statman (2012) emphasized the Keynes' view as sentiment may lead to economic crises. Moreover, in the literature; Baur, Quintero and Stevens (1998), Zouaoui, Nouyrigat and Beer (2011) and Bolaman and Mandaci (2014) found there is an effect of investor sentiment on the market returns during the crises periods. However, to the best of the authors' knowledge, none of these studies investigated power and sign of this effect of investor sentiment on the stock market returns during the crises periods. Therefore, it is expected that the effect of sentiment is high during these periods, and it is hypothesized that there is a negative relationship between investor sentiment and future BIST-100 index returns. The first hypothesis of the thesis can stated as follow:

H1: There is a significant and negative relationship between investor sentiment and future index returns.

Moreover, since the whole period includes all the sample from no crisis, local and international crisis periods, the effect of investor sentiment in each period will be combined in this period and it is expected to be higher. Therefore, it is hypothesized that the effect of investor sentiment is higher in the whole period relative to the crisis periods. The second hypothesis of the thesis is stated as below.

H2: The effect of investor sentiment is more significant and higher in the whole period relative to the local and international crisis periods.

Furthermore, during the local crisis since investors have alternatives to invest in other countries' markets, it is expected that the effect of investor sentiment would be higher during these times. Hence, it is also hypothesized that the effect of investor sentiment is higher in the local crisis periods relative to the international crisis periods. The third hypothesis of the thesis is as follows.

H3: The effect of investor sentiment is more significant and higher in the local crisis periods relative to the international crisis periods.

Moreover, different from the existing studies, Carrion-i-Silvestre et al. (2009) unit root test is applied which considers the structural breaks, and macroeconomic factors such as change in the industrial production index, change in the consumer price index and change in exchange rate are included in the analysis as control variables to eliminate their possible effect on investor sentiment.

Therefore, this thesis may shed light to the literature in terms of finding the probable effects of investor sentiment on stock returns during the crisis periods, which will provide an insight about the irrational behavior of investors during these times in Borsa Istanbul. Moreover, it is believed that this study will have a significant contribution to investors, portfolio managers and policy makers by providing evidence on the effect of investor sentiment on the stock market, namely Borsa Istanbul, and its persistence during financial crises and whether this effect differs based on the origin of the crisis as local or international.

3.2. DATA AND SAMPLE

Investor sentiment proxies' data include monthly observations on closed-end fund discount, mutual fund flows, turnover ratio, share of equity issues in aggregate issues, repo shares in mutual fund portfolios, and volatility premium between the periods January 1997 and November 2017. The calculation of each sentiment proxy is described below.

3.2.1. Closed-End Fund Discount

As stated by Lee, Shleifer and Thaler (1991:106), change in the value-weighted index of closed end fund discounts ($CEFD_t$) are high when investors are pessimistic (negative sentiment) about future returns and low when investors are optimistic (positive sentiment). In other words, the more optimist investors feel, the smaller the discounts of the closed end funds will be (Halkos, 2005:22).

Following Lee, Shleifer and Thaler (1991:87) value weighted index of discounts (VWD) in month t are calculated using the following formulas:

$$VWD_t = \sum_{i=1}^{n_t} W_t DISC_{it} \quad (1)$$

where;

$$W_t = \frac{NAV_{it}}{\sum_{i=1}^{n_t} NAV_{it}} \quad (2)$$

$$DISC_{it} = \frac{NAV_{it} - SP_{it}}{NAV_{it}} \times 100 \quad (3)$$

In Equation (1), n_t indicates the number of funds with available $DISC_{it}$ and NAV_{it} data at the end of month t. In Equations (2) and (3), W_t denotes weight of net asset value (NAV) at the end of month t, and NAV_{it} shows the per share net asset value at the end of month t. In Equation (3), $DISC_{it}$ is the per share discount rate at the end of month t, and SP_{it} is the stock price at the end of month t.

In the second stage, changes in the value-weighted index of discounts (ΔVWD) are calculated with the following equation and it is used as a proxy for investor sentiment:

$$\Delta VWD_t = VWD_t - VWD_{t-1} \quad (4)$$

In Equation (4), VWD_{t-1} shows the value weighted index of discounts in the previous month. The monthly closed end funds data were obtained from Capital Market Board (CMB) monthly bulletins. In Turkey, investment companies (investment trusts) were used as closed-end funds by researchers (i.e. Canbaş and Kandır, 2007; Kaya, 2017). Since there were missing values for the months December 1997 and March 1999, the average of the series was calculated, and the average value was used for these two months. Mean substitution method for dealing with missing values is a common technique in data analysis (Hair, et al., 2009: 52). After substituting two missing values, there are 251 values in total during the period between January 1997 and November 2017.

3.2.2. Mutual Fund Flows

Mutual fund investors are generally considered as small and uninformed in the market because their investments are managed by fund managers (Indro, 2004:105). Therefore, mutual fund flows reflect the level of investor sentiment of uninformed investors in the market. Flows are higher when individual investors become more bullish, so mutual fund flows are considered as positively related with sentiment (Canbas and Kandir, 2009:39).

Sirri and Tufano (1998:1594) defined net flows (FLOW) as the net growth in fund assets. Following them, mutual fund flows (FLOW) are calculated using the following formula:

$$FLOW_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1+R_{i,t})}{TNA_{i,t-1}} \qquad (5)$$

In Equation (5), $FLOW_{i,t}$ is the flow of fund i at the end of month t, $TNA_{i,t}$ is the total net assets of fund i at the end of month t, $TNA_{i,t-1}$ is the total net assets of fund i at the end of previous month, and $R_{i,t}$ is the return of fund i at the end of month t. $R_{i,t}$ is calculated as follows:

$$R_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1 \qquad (6)$$

In Equation (6), $P_{i,t}$ and $P_{i,t-1}$ indicates the share prices of fund i at the end of month t and the previous month respectively.

In the last stage the average flow of all mutual funds ($AFLOW_t$) is computed, and it is used as a proxy for investor sentiment:

$$AFLOW_t = \frac{1}{n}\sum_{i=1}^{n} FLOW_{i,t} \tag{7}$$

In Equation (7); n is the total number of mutual funds at the end of month t.

The monthly mutual funds data were obtained from the CMB monthly bulletins. Because the focus of this study is the stock market, only the A-type mutual funds are obligated to hold at least 25 percent of their holdings as stocks by law were taken into consideration. Hence in the present study, the A-type mutual fund data is used for mutual fund flow calculations. Since there were missing values for December 1997, January 1998 and November 2004, the average of the series was calculated, and the average value was used for these three months following Hair, et al. (2009: 52). After substituting three missing values, there are 251 values in total during the period between January 1997 and November 2017.

3.2.3. Turnover Ratio

Baker and Stein (2004:282) indicated that in a market with short sale constraints, irrational investors trade more when they are optimistic or in other words when their market valuation is higher than those of rational investors. Therefore, market liquidity which is measured by turnover ratio is a positive indicator of investor sentiment.

BIST monthly turnover ratio ($TURN_t$) is obtained by dividing the trading volume of the BIST by the market value of the BIST at month t. Turnover ratio data is available on the CMB monthly bulletins directly. There were no missing values and there are 251 values in total available during the period between January 1997 and November 2017.

3.2.4. Share of Equity Issues in Aggregate Issues

As emphasized by Baker and Wurgler (2000:2248) and Baker and Stein (2004:288), when the market is overvalued by the irrational investors, managers issue equity to time the market. When the market value is too low, they generally prefer debt financing. Therefore, when sentiment is high the market will be overvalued, and the share of equity issues in aggregate issues will increase.

The share of equity issues in aggregate issues is calculated by dividing the total share issues at month t to the total issues using the following formula:

$$EQUITY_t = \frac{ISSUES_t}{TOTAL_t} \tag{8}$$

In Equation (8); $ISSUES_t$ denotes total share issues at month t, and $TOTAL_t$ is the total issues at month t. The monthly data was obtained from CMB monthly bulletins, and there were 251 values in total with no missing data.

3.2.5. Repo Shares in Mutual Fund Portfolios

Brown and Cliff (2004:12) suggested that the amount of cash holdings in the mutual fund assets may be an indicator of investor sentiment. They pointed out that when fund managers are more optimistic about the market, they tend to hold relatively little cash on their portfolios.

In Turkey, mutual funds do not hold cash, but instead they hold reverse repos in their portfolios. Therefore, following Canbas and Kandir (2009:40), share of repo holdings in mutual fund portfolios were used as a proxy for investor sentiment in this study. In contrast to the cash holdings and repo holdings, the amount of reverse repo holdings is positively related with investor sentiment. When fund managers are more optimistic about the market, they hold more reverse repos in their portfolios with the thought of selling them to the market when the value of reverse repos increase. The monthly data was obtained from the CMB monthly bulletins. The data on reverse repo shares started to be issued by mutual fund managers at the beginning of July 1997, and for that reason between the months of January and July the values were exhibited as zero. There were 245 values in total during the period between January 1997 and November 2017.

3.2.6. Volatility Premium

While forming an investor sentiment index, in their initial paper Baker and Wurgler (2006) used dividend premium as one of the proxies of investor sentiment. The rationale behind using dividend premium is the fact that dividend paying firms are perceived as less risky and more profitable firms. Baker and Wurgler (2006:1656) emphasized that there is an inverse relationship between dividend premium and investor sentiment, because when investors are pessimistic, they prefer safer investments, so the dividend premium increases.

However, in another paper, Baker, Wurgler and Yuan (2012:274) pointed out that since dividends are relatively uncommon in some countries, dividend premium cannot be used as a proxy. For that reason, in their study, they used volatility premium instead. Volatility premium is inversely and highly correlated with dividend premium, and hence it is a positive indicator of investor sentiment. When sentiment is low (more pessimistic investors), investors prefer less risky stocks, so high-volatile or non-dividend paying stocks are undervalued, and the premium between high and low volatile stocks shrinks. In contrast, when investors are more optimistic about the market, investors prefer more volatile stocks, so they are relatively overvalued, and the premium goes up (Baker and Wurgler, 2006).

The volatility premium was calculated by following Baker, Wurgler and Yuan (2012:274). First, the volatilities of stocks were calculated by the standard deviation of the trailing 12 months of monthly returns. Then, two portfolios were constructed for each month as high volatility stocks and low volatility stocks. High (low) volatility portfolio is composed of the stocks that have top (bottom) 30% highest (lowest) variances in month t. Finally, volatility premium ($VOLP_t$) is the log difference between the average market-to-book ratio of high volatility stocks and that of low volatility stocks.

The market-to-book ratio and variances data of the non-financial stocks were obtained from the Finnet database. There were totally 110 stocks in the initial month

(January 1997), and this number reached 241 stocks at the end of the period (November 2017). Totally, there are 251 volatility premium values during the period between January 1997 and November 2017.

3.3. METHODOLOGY

To form an investor sentiment index, in this study, Baker and Wurgler (2006) procedure is followed. Similarly, Baker and Wurgler (2006) sentiment index is also composed of six proxies. These proxies are the closed-end fund discount, turnover ratio, the number and average first-day returns on IPOs, share of equity issues in aggregate issues, and the dividend premium. Due to country-based differences some of these proxies, such as the number and average first-day returns on IPOs and the dividend premium, were not used in this study, but based on the related literature and data availability some additional proxies were added such as mutual fund flows, repo shares in mutual fund portfolios and volatility premium.

Following Baker and Wurgler (2006) methodology, principal component of the six proxies and their lags were taken into consideration. Lag values of each variable were used because some variables may reflect sentiment earlier than others (lead-lag relationship). This provided initial sentiment index with 12 loadings with the current and lagged values of the proxies.

Following Keleş, et al. (2017: 991), to form an initial sentiment index, weighted average of component loadings was calculated for each proxy. Then, the correlation coefficients between the initial sentiment index and each proxy's lag and current values were calculated. Then, the proxies (lag or current) which have the higher and positive correlation with the initial sentiment index was selected to be used in the formation of the final sentiment index. As the selection criteria to be included in the final sentiment index, higher absolute values of correlation coefficients were used following Yang and Hasuike (2017: 25). Finally, an investor sentiment index was constructed by calculating the weighted average of each selected lagged or current proxy.

3.4. EMPIRICAL RESULTS

First, the descriptive statistics of the proxies were examined as shown in Table 1. The results show that during 1997 to 2017, there are 251 monthly observations in total. Change in the value-weighted closed-end fund discount ($CEFD_t$) ranges between -38.85 and 30.43 with mean of -0.052 and standard deviation of 8.915. Average mutual fund flows ($AFLOW_t$) ranges between -51.48 and 41.68 with mean of 0.21 and standard deviation of 4.62. Turnover ratio ($TURN_t$) ranges between 5.20 and 34.12 with mean of 13.44 and standard deviation of 3.751. Share of equity issues in aggregate issues ($EQUITY_t$) ranges between 0 and 1 with the lowest standard deviation of 0.352 and mean of 0.36. Hence it could be stated that $EQUITY_t$ dataset is more concentrated around the mean relative to the other proxies. Reverse repo shares ($REPO_t$) ranges between 0 and 86.15 with the highest standard deviation of 20.36 and mean of 42.61. Thus, it could be stated that variation of the repo shares is the highest among the variables. Finally, volatility premium ($VOLP_t$) ranges between -1.25 and 5.74 with mean of 0.88 and standard deviation of 0.839.

Table 1. Descriptive Statistics of the Proxies

This table presents the results of the descriptive statistics. $CEFD_t$ is the closed-end fund discount, $AFLOW_t$ is mutual fund flows, $TURN_t$ is the turnover ratio, $EQUITY_t$ is the share of equity issues in aggregate issues, $REPO_t$ is the repo shares in mutual fund portfolios, and $VOLP_t$ is the volatility premium, at month t.

Statistics	$CEFD_t$	$AFLOW_t$	$TURN_t$	$EQUITY_t$	$REPO_t$	$VOLP_t$
N	251	251	251	251	251	251
Mean	-0.0519	.205	13.440	.355	42.613	.876
Std. Dev.	8.915	4.628	3.751	.352	20.360	.839
Min.	-38.85	-51.48	5.20	0.00	0.00	-1.25
Max.	30.43	41.68	34.12	1.00	86.15	5.74

Second, the normality of each variable is checked by the Kolmogorov-Smirnov Normality Test. According to Kolmogorov-Smirnov test, if the statistic results are statistically significant, the null hypothesis that the variables are normally distributed is rejected. As shown in Table 2, the statistics are statistically significant, therefore it could be stated that all the variables are not normally distributed. If the data is not normally distributed, the Principal Component Method for estimating factors should be used.

Table 2. Test of Normality

This table presents the results of the Kolmogorov-Smirnov normality test results. $CEFD_t$ is the closed-end fund discount, $AFLOW_t$ is mutual fund flows, $TURN_t$ is the turnover ratio, $EQUITY_t$ is the share of equity issues in aggregate issues, $REPO_t$ is the repo shares in mutual fund portfolios, and $VOLP_t$ is the volatility premium, at month t. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Statistics	$CEFD_t$	$AFLOW_t$	$TURN_t$	$EQUITY_t$	$REPO_t$	$VOLP_t$
N	251	251	251	251	251	251
Kolmogorov-Smirnov Test	.121***	.402***	.076***	.174***	.074***	.200***

After those diagnostic tests, following Baker and Wurgler (2006), principal component of the six proxies and their lags were estimated. Lag values of each variable were used because timing of some variables may differ, in other words some of them may forecast sentiment earlier than others. Before constructing the 12 loadings initial investor sentiment index (tSENT), KMO and Barlett's tests were conducted to verify whether the data is factorable or not. KMO score should be 0.50 or higher to proceed with factor analysis (Hair, et al. 2009: 103). According to Table 3, in this data set, KMO score is 0.589 which is an acceptable level to conduct factor analysis. Moreover, Bartlett's test must be significant to be considered as factorable, and in this data set $p<0.05$, hence it is statistically significant.

Table 3. KMO and Barlett's Test (tSENT)

This table presents the results of Kaiser-Meyer-Olkin (KMO) and Barlett's Test of Sphericity test results of the initial sentiment index (tSENT).

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.589
Barlett's Test of Sphericity	**Approx. Chi-Square**	1119.226
	df	66
	Sig.	0.000

The given statistics show that the dataset can be used in the principal component analysis. To detect the number of components that the dataset has, eigenvalues shall be evaluated. Table 4 shows that there are five components, and these factors have eigenvalues over 1. As a whole, the components explain 70% of the sample variance of the variables. The components contribute this cumulative ratio with the ratio of 21%, 17%, 13%, 10% and 9% respectively.

Table 4. Total Variance Explained (tSENT)

This table presents the total variance explained of the initial sentiment index (tSENT).

Component	Eigenvalue	Contribution Ratio (%)	Cumulative Contribution Ratio (%)
1	2.513	20.939	20.939
2	2.001	16.675	37.614
3	1.565	13.039	50.653
4	1.231	10.255	60.908
5	1.065	8.872	69.780

Moreover, Figure 1 presents the graph of eigenvalues in the scree plot, where the horizontal axis shows the number of the component and the vertical axis shows eigenvalues. As it is observed in the scree plot, after five components the graph becomes flatter, so it is appropriate to choose five components which is consistent with the results that were shown in Table 4.

Figure 1. Eigenvalues Graph (tSENT)

Table 5 shows the loadings of each component, and to form an initial index (tSENT), the weighted average of each component from 1 to 5 was calculated for each proxy using Equation (9):

$$Weighted\ Average_i : \frac{Component_n \times Contribution\ Ratio_n}{69.780} \quad (9)$$

In Equation (9), weighted average of each proxy was calculated by multiplying each component value with its respective contribution ratio and dividing the value by the cumulative contribution ratio of the five components which is indicated as 69.780 in Table 4.

With the indicated weighted averages in Table 5, the initial investor sentiment index was defined as follows:

$$tSENT_t = 0.11CEFD_t + 0.14AFLOW_t + 0.14TURN_t + 0.05EQUITY_t + 0.32REPO_t + 0.22VOLP_t - 0.13CEFD_{t-1} + 0.09AFLOW_{t-1} + 0.14TURN_{t-1} + 0.06EQUITY_{t-1} + 0.33REPO_{t-1} + 0.24VOLP_{t-1} \quad (10)$$

With the help of Equation (10), the higher absolute values of correlation coefficients of the variables were selected while determining the lagged or current values to form a final investor sentiment index. The indicated coefficients show the correlation of each variable with the initial sentiment index in Table 5. As a result, $TURN_t$ (0.14=0.14) has the same correlation with its lagged value, so the current value was selected. Moreover, $AFLOW_t$ (0.14>0.09), $CEFD_{t-1}$ (0.13>0.11), $EQUITY_{t-1}$ (0.06>0.05), $REPO_{t-1}$ (0.33>0.32) and $VOLP_{t-1}$ (0.24 > 0.22) were selected. Therefore, while the current values of mutual fund flows and turnover rate data reflect investor sentiment; lagged values of the closed-end fund discount, share of equity issues in aggregate issues, repo shares in mutual fund portfolios and volatility premium reflect investor sentiment better relative to their current values.

Table 5. Component Matrix (tSENT)

This table presents the results of each components. $CEFD_t$ is the closed-end fund discount, $AFLOW_t$ is mutual fund flows, $TURN_t$ is the turnover ratio, $EQUITY_t$ is the share of equity issues in aggregate issues, $REPO_t$ is the repo shares in mutual fund portfolios, and $VOLP_t$ is the volatility premium, at month t. $CEFD_{t-1}$ is the closed-end fund discount, $AFLOW_{t-1}$ is mutual fund flows, $TURN_{t-1}$ is the turnover ratio, $EQUITY_{t-1}$ is the share of equity issues in aggregate issues, $REPO_{t-1}$ is the repo shares in mutual fund portfolios, and $VOLP_{t-1}$ is the volatility premium, at the preceding month.

Variables	**Components**					
	1	2	3	4	5	**Weighted Avg.**
$CEFD_t$	-0,010	0,019	-0,074	0,051	0,925	**0,11**
$AFLOW_t$	-0,001	-0,021	0,096	0,730	0,157	**0,14**
$TURN_t$	-0,062	0,038	0,798	0,106	-0,206	**0,14**
$EQUITY_t$	0,630	-0,391	-0,130	-0,159	0,000	**0,05**
$REPO_t$	0,920	0,204	-0,057	0,065	0,003	**0,32**
$VOLP_t$	0,035	0,892	0,037	-0,034	-0,063	**0,22**
$CEFD_{t-1}$	-0,015	-0,065	-0,557	0,229	-0,333	**-0,13**
$AFLOW_{t-1}$	-0,031	0,013	0,019	0,743	-0,126	**0,09**
$TURN_{t-1}$	-0,101	0,017	0,760	0,165	-0,026	**0,14**
$EQUITY_{t-1}$	0,653	-0,463	-0,026	-0,132	0,012	**0,06**
$REPO_{t-1}$	0,907	0,237	-0,032	0,063	-0,013	**0,33**
$VOLP_{t-1}$	0,050	0,856	0,040	-0,019	0,099	**0,24**

After specifying the final list of proxies to be included in the sentiment index, the final investor sentiment index, which will be used in the analysis as an investor sentiment proxy, was constructed.

First, KMO and Barlett's tests were conducted to verify whether the data is factorable or not. Even though the Barlett's test is statistically significant, KMO results is 0.419 which is lower than 0.50. Hence the data is not factorable which leads to the need to remove one or several variables from the principal component analysis. Consequently, after analyzing the effect of removal of each variable on the KMO and Barlett's tests results, lagged value of volatility premium ($VOLP_t$) is removed from the analysis. Disposing volatility premium from the analysis, as presented in Table 6, increased the KMO test result to 0.513 which shows that the remaining five variables are factorable, so principal component analysis could be implemented to form an index. Furthermore, as shown in Table 6, the Barlett's test is statistically significant.

Table 6. KMO and Barlett's Test (SENT)

This table presents the results of Kaiser-Meyer-Olkin (KMO) and Barlett's Test of Sphericity test results of the final sentiment index (SENT).

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.513
Barlett's Test of Sphericity	**Approx. Chi-Square**	47.239
	df	10
	Sifg.	0.000

To detect the number of components that the dataset has, eigenvalues are also evaluated. Table 7 shows that there are two components, and these factors have eigenvalues over 1. Totally, the components explain 52% of the sample variance of the variables. The components contribute this cumulative ratio with the ratio of 27% and 24%, respectively.

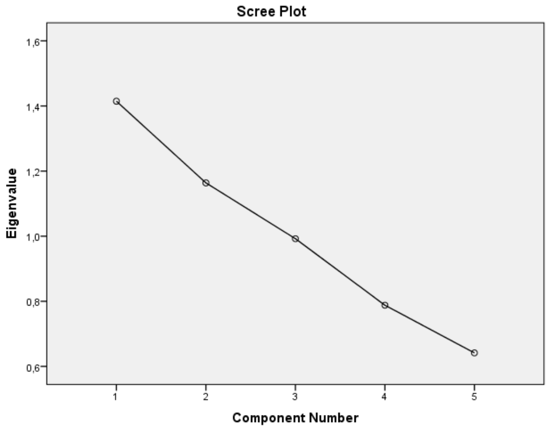
Table 7. Total Variance Explained (SENT)

This table presents the total variance explained of the final sentiment index (SENT).

Component	**Eigenvalue**	**Contribution Ratio (%)**	**Cumulative Contribution Ratio (%)**
1	1.364	27.283	27.283
2	1.214	24.284	51.566

Moreover, Figure 2 shows the graph of eigenvalues in the scree plot, where the horizontal axis shows the number of the component and the vertical axis shows the eigenvalues. As it is observed in the scree plot, after two factors the eigenvalues fall under the value of one, so it is appropriate to choose two components which are consistent with the results that were shown in Table 7.

Figure 2. Eigenvalues Graph (SENT)



As shown in Table 8, first two principal components and the five proxies were used to construct the investor sentiment index using the results in the component matrix (SENT). Each component is defined as shown in equation (11) and (12).

$$Component\ 1 = -0.029CEFD_{t-1} + 0.037\mathrm{A}FLOW_t - 0.150TURN_t + 0.821EQUITY_{t-1} + 0.815\mathrm{REPO}_{t-1} \quad (11)$$

$$Component\ 2 = -0.661CEFD_{t-1} + 0.460\mathrm{A}FLOW_t + 0.752TURN_t - 0.031EQUITY_{t-1} + 0.001\mathrm{REPO}_{t-1} \quad (12)$$

The investor sentiment is modelled by calculating weighted averages of two components and summing them up as follows:

$$SENT_t = \frac{0.273}{0.516}Component1 + \frac{0.243}{0.516}Component2 \quad (13)$$

In Equation (13), $SENT_t$ is the total investor sentiment at month t. 0.273 and 0.243 are the contribution ratios of component 1 and 2, respectively. 0.516 is the cumulative contribution ratio of the two components as shown in Table 7.

Table 8. Component Matrix (SENT)

This table presents the results of each components. $CEFD_{t-1}$ is the closed-end fund discount at the preceding month, $AFLOW_t$ is mutual fund flows at month t, $TURN_t$ is the turnover ratio at month t, $EQUITY_{t-1}$ is the share of equity issues in aggregate issues at the preceding month and $REPO_{t-1}$ is the repo shares in mutual fund portfolios at the preceding month.

Variables	Components		
	1	2	**Weighted Avg.**
$CEFD_{t-1}$	-0,029	-0,661	**-0,33**
AFLOW	0,037	0,460	**0,24**
TURN	-0,150	0,752	**0,27**
$EQUITY_{t-1}$	0,821	-0,031	**0,42**
$REPO_{t-1}$	0,815	0,001	**0,43**

A linear function of the sentiment proxies is the resulting index which could be formulized as follows:

$$SENT_t = -0.33CEFD_{t-1} + 0.24AFLOW_t + 0.27TURN_t + 0.42EQUITY_{t-1} + 0.43REPO_{t-1} \quad (14)$$

As expected, consistent with the literature, Equation (14) shows that mutual fund flows, turnover ratio, share of equity issues in aggregate issues and repo shares are positively related with the sentiment index, and closed-end fund discount is negatively associated. Table 9 summarizes the expected relationship of each proxy with the investor sentiment and their signs in the constructed investor sentiment index.

Moreover, the variables show lead-lag relationship with investor sentiment index. Based on the correlation values shown in Table 5, the one month lagged data of closed-end fund discount, share of equity issues in aggregate issues and repo shares are found to reflect investor sentiment better than the current month data. On the other hand, current month mutual fund flows and turnover ratio better reflect the investor sentiment. Finally, an investor sentiment index is calculated for each month using Equation (14) for the analysis of the present study. The composite sentiment index will be used to investigate the effect of investor sentiment in the crisis periods for the Turkish stock market in the following chapter.

Table 9. Relationship of Proxies with Investor Sentiment

This table presents the expected relationship of proxies with investor sentiment. CEFD is the closed-end fund discount, AFLOW is mutual fund flows, TURN is the turnover ratio, EQUITY is the share of equity issues in aggregate issues and REPO is the repo shares in mutual fund portfolios.

Proxy	Examples of Studies	Relationship with Investor Sentiment	Investor Sentiment Index
CEFD	Lee, Shleifer and Thaler (1991), Brown (1999), Halkos (2005)	−	−
AFLOW	Warther (1995), Lee, et al. (2002), Kumar and Ng (2011)	+	+
TURN	Baker and Stein (2004), Baker and Wurgler (2007)	+	+
EQUITY	Stambaugh, Yu and Yuan (2012), Baker and Wurgler (2006)	+	+
REPO	Brown and Cliff (2004b), Simutin (2014), Canbaş and Kandır (2009)	+	+

CHAPTER FOUR
INVESTOR SENTIMENT IN THE CRISIS PERIODS

In the first chapter, the investor sentiment literature was examined in detail, and it was observed that there is a gap in the literature about the effect of investor sentiment on stock markets during the crisis periods. For that reason, the main aim of this study is to analyze the effect of investor sentiment on Borsa Istanbul for the crisis periods between 1997 and 2017 using the investor sentiment index constructed in the previous chapter.

For this purpose; first the CMAX crisis indicator is used to detect the crisis periods in Turkey, and the detected crises are separated as local and international; to analyze if the pattern of investor sentiment differs between the crises based on their origin being local or international. Second; regression analysis is employed to investigate the effect of investor sentiment during the determined crisis periods. Last; as robustness check of the constructed investor sentiment index, the six sentiment proxies are used separately to repeat the regression analysis.

In this chapter, in the first part the CMAX methodology will be defined. In the second part, the crises in Turkey will be detected and explained. In the third part, the data will be defined, and the related methodology will be covered in detail. In the fourth part, empirical findings of the regression analysis will be presented. In the last part, robustness tests will be applied for the comparison of investor sentiment proxies with the constructed index.

4.1. CMAX METHODOLOGY

To identify the crises, CMAX indicator was first introduced by Patel and Sarkar (1998). It is also widely used by equity market practitioners and included in financial media such as the publication of Morgan Stanley ("MSCI Perspective") and the Forbes magazine (Barra-Forbes page) (Patel and Sarkar, 1998: 264).

Under the CMAX methodology, a crisis in the stock market is determined by comparing the current value of a market index to its maximum value over the previous T periods, usually one or two years. In this study, two years were used.

Following Patel and Sarkar (1998:265); the CMAX indicator at time t is calculated as follows:

$$CMAX_t = \frac{P_{m,t}}{\max(P_{m,t-24},\ldots\ldots,P_{m,t})} \quad (15)$$

In equation (15), $P_{m,t}$ indicates the current closing value of the market index at time t. BIST 100 index monthly closing values were collected for the period 1995-2017 to be able to calculate the crisis periods beginning from the year 1997. The trigger level of a crisis can be chosen as 2, 1.5 or 1 standard deviations below the mean of the series. When the index decreases under this trigger level, a crisis is observed. Patel and Sarkar (1998: 265) indicated that for the developed markets, setting the trigger level at 2 standard deviations below the mean would be appropriate. However, for the developing markets, they stated that since they have higher volatility, this level should be 1 standard deviation (Patel and Sarkar, 1998: 265). Therefore, in this study, since Turkey is a developing market which is more volatile relative to the developed markets and to capture all known crisis periods, the trigger level is set as 1 standard deviation below the mean. That is;

$$\text{If } CMAX_t < \overline{CMAX} - \sigma_m \text{ ; } C_t = 1, \text{ otherwise, } C_t = 0 \quad (16)$$

In equation (16), $\overline{CMAX}$ indicates the mean, σ_m indicates the standard deviation of the market, and C_t shows the stock market crisis indicator at month t.

To sum up, if $CMAX_t$ equals 1, it indicates price increases over the period. If prices decrease, $CMAX_t$ is closer to 0. As equation (16) shows, a crisis is detected when $CMAX_t$ drops below a threshold level which is the mean of $CMAX_t$ minus one standard deviation, hence crisis dummy variable (C_t) equals 1.

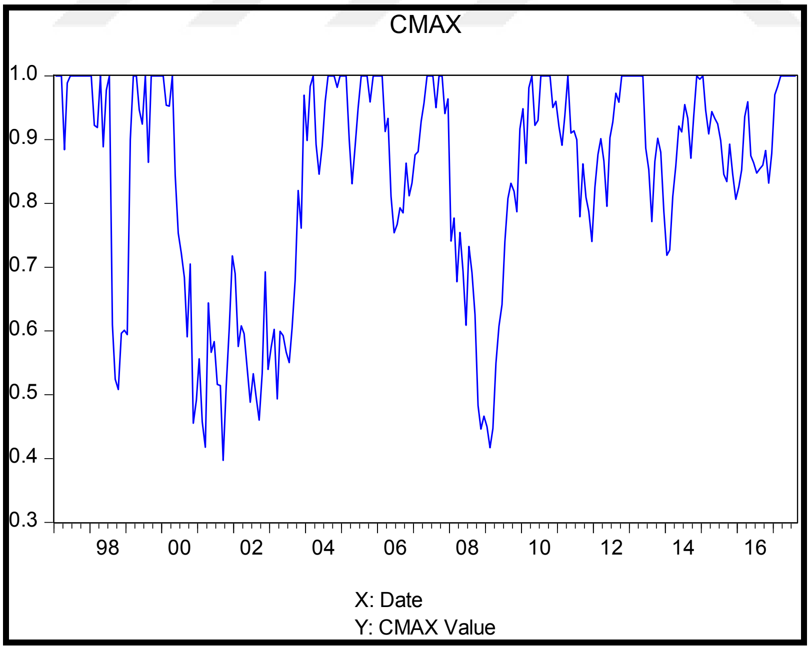
Patel and Sarkar (1998: 265) also defined the pre-crisis period (the start of the crisis) as the point where the price reaches its historical maximum level (peak point) over a 2-year period; and the post-crisis period (the date of the recovery) is defined as the first month after the crisis when the index reaches the pre-crises maximum value.

4.2. CRISES IN TURKEY

Considering the above explanations, by implementing CMAX methodology, the crisis periods in BIST were determined as presented in Figure 3. The vertical axis in the figure shows the dates as months/years and the horizontal axis shows the CMAX values associated with the month. Over the period between 1997 and 2017, three crises were detected. First crisis period is observed from August 1998 to January 1999; second crisis period is observed from September 2000 to August 2003; and the last one is observed from September 2008 to June 2009.

These three crisis periods could be separated as international and local financial crises. Among the three crisis periods determined, the period from September 2000 to August 2003 corresponds with the 2001 Turkish financial crisis which can be categorized as local. Other two crisis periods correspond with the 1997 Asian and 1998 Russian financial crises, and 2008 global financial crisis, respectively. All these crises can be categorized as international crises.

Figure 3. Crisis Periods in BIST



4.2.1. 1997 Asian and 1998 Russian Crises

First crisis period corresponds to the 1997 Asian financial crisis which is followed by the 1998 Russian financial crisis. For this period, the pre-crisis period in Borsa Istanbul starts in July 1998 and ends in August 1998, and the post-crisis period is between February 1999 and March 1999.

In 1997, because of flight of capital from Far East and Southeast Asian Countries, high devaluations had occurred, oil prices had crashed, and the crisis had started initially in Thailand followed by other Asian countries which are named as Asian Tigers. In 1998, the crisis had spread to Russia. Consequently, they announced moratorium and the ruble has devalued. Russian market has shrunk, flight of capital has occurred, and loan interest rates has increased (Kazgan, 2013:22).

Because of the globalization in financial markets, Asian crisis overspread to other countries, and the systematic risk in these countries increased sharply. Turkey was also affected from the Asian crisis which is followed by the Russian crisis in the middle of 1998 (Kazgan, 2013: 223). Because of the appreciation of the U.S. dollar, Turkish lira (TL) lost value and that affected Borsa Istanbul, too. The value of BIST 100 index decreased and the foreign investors sold out their holdings (Uzun, 2003:167). In these times, Turkey experienced devaluation of Turkish Lira, an increase in imports, growth in external debt, high unemployment and increase in inflation rates (Fırat, 2009). In October 1998, early election decision was taken and BIST 100 index started to go up. In February 1999, Abdullah Ocalan who is the head of a separatist terror organization was captured, and this event brought confidence to the foreign investors, so the trading volume and the index value of Borsa Istanbul has increased (Uzun, 2003: 168). Therefore, after these times the effect of Asian crisis has disappeared (Uzun, 2003: 168).

4.2.2. 2001 Turkish Financial Crisis

The second crisis period determined by the CMAX methodology corresponds to the 2001 Turkish financial crisis. For this period, pre-crisis period starts in April 2000 and ends in August 2000. The Index has reached its pre-crisis maximum value in March 2004, therefore post-crises period contains the months between September 2003 and March 2004.

During these times, there were two crises; the first one occurred in November 2000 and the second one occurred in February 2001. Following the after effects of the 1997 Asian and 1998 Russian crises, at the end of 1999, Turkey faced economic difficulties such as the decrease in growth rates, high inflation rates (around 70%), and budget deficits. In 2000, to decrease the inflation rate and to provide sustainable growth, stand by arrangement program was put into effect with International Monetary Fund (IMF) (Eğilmez, 2008: 74).

Initially, the program succeeded to bring down the interest and inflation rates, but after 11 months, Turkey faced a severe liquidity shortage and in November 2000 liquidity crisis arose which resulted in sudden capital outflows (Temiz and Gökmen, 2009:3). During the crisis, current account and trade deficits grew, Turkish lira devalued, and the growth rate declined considerably (Temiz and Gökmen, 2009: 2). On 19 February 2001, a controversy was experienced between the president and the prime minister of Turkey at the National Security Council. Since the Turkish economy had not recovered fully from the November 2000 crisis yet, this event led to higher levels of uncertainty in the market and foreign investors to pull out of the market, and the interest rates continued to increase sharply (Kepenek and Yentürk, 2011: 593). Because of this crisis, the confidence to the financial system decreased, current account deficit increased, the value of the stock market decreased, unemployment and inflation rates increased, and many firms went bankrupt. Therefore, it could be stated that 2001 crisis is the most intensive crisis of the history of the Republic of Turkey (Turan, 2011: 75).

With the crisis, initially Turkey left the crawling peg system and floating exchange rate regime has been accepted. In June 2001, transition to the strong economy program, which covered the years 2001-2004, has been introduced and with that program austerity policies such as strengthening the banking sector or reducing public non-interest budget surplus has been implemented to recover (Kepenek and Yentürk, 2011: 594).

4.2.3. 2008 Global Crisis

Last crisis period determined by the CMAX method corresponds to the 2008 global financial crisis. For this period, the pre-crisis period is between October 2007 and August 2008. The Index has reached its pre-crisis maximum value in April 2010, so the post-crisis period is between July 2009 and April 2010. With the increase in the subprime mortgages that was given to the less creditworthy borrowers, the housing bubble burst because of the borrowers' failure to pay back the credits, and this led to the start of the global financial crisis in the U.S.. The crisis spread to the mortgage companies and investment banks, and to the financial products, such as hedge funds, that invested in mortgage-based securities (Orlowski, 2008: 2). The global financial crisis that is accepted as the most severe crisis since the Great Depression of the 1930s, caused a collapse of some of the biggest financial institutions, such as Lehman Brothers (Helleiner, 2011: 68).

As emphasized by Eğilmez (2008:69); the crisis affected many developing markets because of several reasons. Initially, the hot money flows to these countries reduced. Secondly, decrease in the growth rate in developed countries lead to decreases in demand, and hence their imports from developing countries also decreased. This situation resulted in a decrease in foreign trade income of developing countries, and recession started. Thirdly, because of these occurrences, oil and metal prices decreased sharply. These events caused deflationary effects in many countries (Eğilmez, 2008:69). Turkey is one of the countries that was affected from the global financial crisis. In the first quarter of 2008, the growth rate of Turkey increased. For that reason, it was thought that Turkey was not affected, however, in the last quarter of 2008, downfall had started almost in all the sectors. Moreover, Gross Domestic Product (GDP), growth and the employment rates dropped, and foreign trade deficit rose sharply (Kazgan, 2013: 282).

4.3. DATA AND METHODOLOGY

The following regression equation is applied to detect the effect of investor sentiment on the future stock market returns proxied by the BIST 100 index.

$$R_t = \alpha + \beta_1 SENT_{t-1} + \varepsilon \quad (17)$$

In equation (17); R_t is the return of BIST 100 index at month t, $SENT_{t-1}$ is the composite sentiment index at the preceding month and ε is the error term. As discussed in Chapter 3, the sentiment index was constructed by taking first principal component of five investor sentiment proxies (closed-end fund discount, mutual fund flows, turnover ratio, share of equity issues in aggregate issues, and repo shares in mutual fund portfolios). Moreover, the return on the BIST 100 index is calculated as follows:

$$R_t = \ln(P_t / P_{t-1}) \quad (18)$$

In equation (18); R_t is the return of BIST 100 index at time t, P_t is the closing value of BIST 100 index at time t, and P_{t-1} is the closing value of BIST 100 index in the preceding month.

Since there is a possibility that investor sentiment can be affected by economic factors, chosen factors are included into the analysis as control variables. The determined economic control variables are the change in the industrial production index, consumer price index and the change in the exchange rate ($) which were selected based on the related literature.

Industrial production index (IPI) is defined by The Organization for Economic Co-operation and Development (OECD) (2018) as the output of industrial establishments such as mining, manufacturing, electricity, gas, steam and air conditioning supply, and it indicates change in the volume of production output relative to a base year. Chen, Roll and Ross (1986) specified that industrial production affect stock returns significantly. Similarly, in Turkey, the effect of industrial production index on stock market is found to be statistically significant (Büyükşalvarcı and Abdioğlu, 2010; Muradoglu, Taskin and Bigan, 2000). The seasonally and calendar adjusted IPI data is obtained from the Turkish Statistical Institute website, and there are 250 observations in total.

Consumer price index (CPI) is a widely used measure of inflation and OECD (2018) defines it as “the change in the prices of a basket of goods and services that are typically purchased by specific groups of households”. Fama (1981) designated that stock returns and inflation has a significant relationship. In Turkey, there are several studies that found significant relationship between inflation and stock market (i.e. Kandır, 2008; Karacaer and Kapusuzoğlu, 2010). The change (%) in the CPI data is obtained from the Turkish Statistical Institute website, and there are 250 observations in total.

Mukherjee and Naka (1995) and Ajayi and Mougoue (1996) found a long run relationship between stock market and exchange rates, therefore change in the exchange rate (XR) was also used as a control variable. Identically, in Turkey, stock market and exchange rates have a significant relationship (Aydemir and Demirhan, 2009; Kandır, 2008; Kasman, 2003) The exchange rate used is the dollar exchange rate, because of the data availability and its global impact. The monthly dollar exchange rate data is obtained from the Central Bank Republic of Turkey (CBRT) website, and there are 250 observations in total.

Monthly changes in the economic variables, namely, IPI, CPI and XR, were calculated as follows:

$$r_e = (EV_t - EV_{t-1})/EV_{t-1} \tag{19}$$

In Equation (19), r_e indicates the return or change ratio, EV_t indicates the value of the economic variable at the end of month t, and EV_{t-1} indicates the value of the economic variable at the end of the preceding month.

Beside these macroeconomic control variables, structural breaks during the indicated period are also used as control variables and they are included in the regression equation as a dummy variable. As emphasized by Andreou and Ghysels (2009: 840), financial time series are mostly affected from multiple structural breaks and these breaks in turn may affect returns and volatility which are the fundamental financial indicators. Structural breaks are instability points such as war, peace, natural disasters, terrorism, policy changes and economic crisis in the parameters of the forecasting model (Valentinyi-Endrész, 2004: 12). Many studies argued that ignoring structural breaks cause incorrect results about the financial variables (Andreou and Ghysels, 2009; Valentinyi-Endrész, 2004).

Therefore, in this study structural break dates are included into the analysis as a dummy variable. Mostly used structural break tests include Perron (1989), Zivot and Andrews (2002), and Ng and Perron (2003), however these tests could detect one or two breaks in the series. On the other hand, recently developed Carrion-i-Silvestre, et al. (2009) unit root test is able to detect up to five structural break dates. In this study, this test is used to detect the breaks during the period 1997 to 2017. As shown at Table 10, five breaks are detected on BIST 100 index return series which are August 1997, November 1999, November 2002, December 2007 and July 2011.

Table 10. Carrion-i-Silvestre et al. (2009) unit root test

BP indicates the break points.

	BP1	BP2	BP3	BP4	BP5
BIST 100	1997, 8	1999, 11	2002, 11	2007, 12	2011, 7

The detected break dates are mostly clustered around the important economic and political events such as 1997 Asian and 1998 Russian financial crises, November 1999 Düzce Earthquake, 2001 Turkish financial crisis, 2008 global financial crisis and 2011 European debt crisis.

Finally, the following regression model, which includes the control variables along with the sentiment proxy, was developed:

$$R_{\mathrm{t}} = \alpha + \beta_1 SENT_{t-1} + \beta_2 IPI_t + \beta_3 CPI_t + \beta_4 XR_t + \beta_5 DUM + \varepsilon \qquad (20)$$

In Equation (20) R_{t} is the return of BIST 100 index at month t, $SENT_{t-1}$ is the investor sentiment index at the preceding month, IPI_t is the change in the industrial production index at month t, CPI_t is the change in the consumer price index at month t, XR_t is the change in the exchange rate ($) at month t, DUM is the dummy variable for structural breaks, and ε is the error term.

Following the diagnostic tests, the regression equations are tested for the whole period and the crisis periods separately using Eviews software program. The dates of the crisis periods begin with the pre-crises periods and finish with the end of the post-crises periods. To observe the impact of each crisis period; “whole period”, “no crisis period”, “all crisis periods”, “local crisis period” and “international crisis periods” were subjected to the same regression analyses using equation (17) and (20) separately.

4.4. EMPIRICAL RESULTS

In the study, before implementing the regression analysis, first the diagnostic tests are carried out to test whether the assumptions of the regression analysis are met. After the model is corrected based on the findings of the diagnostic tests, the main analyses are done.

4.4.1. Diagnostic Test Results

First, the descriptive statistics of the BIST 100 index return, sentiment index, industrial production index (IPI), consumer price index (CPI), change in the dollar rate (XR), and the structural break dummy (DUM) were examined as shown in Table 11. The sample contains 250 monthly observations for the period February 1997 to November 2017.

BIST 100 index returns range between 0.59 and -0.49, and the mean is 0.017 with standard deviation of 0.118. The index reached its maximum value in December 1999, and it reached its minimum value in August 1998.

The sentiment index values range between 48.45 and -5.83, with a mean of 22.24 and standard deviation of 9.299. The sentiment index reached its maximum value in May 2001, and the minimum value is observed in June 1997.

Change in the industrial production index values range between 0.16 and -0.07 with the mean value of 0.0046 and with the standard deviation of 0.0248. It reached its maximum value in January 2005, and it reached the minimum value in January 2009.

Change in the consumer price index reached its maximum value of 0.103 in April 2004, and its minimum value of -0.014 in June 2011 with the average value of 0.0168 and with the standard deviation of 0.0192.

Change in the dollar exchange rate was maximum in March 2001 at the level of 0.308, and it was minimum in May 2003 at the level of -0.084. The mean of the change in the exchange rate was 0.0152 with the standard deviation of 0.0438.

The values of the dummy variable for the structural break is either 0 or 1, so the maximum and the minimum values are 1 and 0 as expected with mean of 0.02 and standard deviation of 0.1403.

If the standard deviations of the variables are compared, the highest standard deviation was observed in the constructed sentiment index, and it could be argued that the sentiment index has the highest volatility among the variables. Moreover, as shown in Table 11, except the sentiment index, Jarque-Bera test statistics of the other variables are statistically significant at 1 % level which means only the sentiment index data is normally distributed.

Table 11. Descriptive Statistics

This table presents the results of the descriptive statistics. R is the return of BIST100 index, SENT is the investor sentiment index, IPI is the change in the industrial production index, CPI is the change in the consumer price index, XR is the change in the exchange rate ($/TL) and DUM is the dummy for structural breaks. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Variables	Mean	Maximum	Minimum	Standard Dev.	Jarque-Bera	Observations
R	0.0167	0.5866	-0.4948	0.1177	190.51***	250
SENT	22.240	48.445	-5.8292	9.2990	0.6011	250
IPI	0.0046	0.1617	-0.0677	0.0248	408.73***	250
CPI	0.0168	0.1030	-0.0143	0.0192	134.53***	250
XR	0.0152	0.3087	-0.0841	0.0438	1422.08***	250
DUM	0.0200	1.0000	0.0000	0.1403	23072.07***	250

Second, the correlation analysis was carried out to investigate the multicollinearity levels among variables. As presented in Table 12, there is no multicollinearity problem detected among the variables, because all the correlations are below 50%.

Table 12. Pearson Correlation Matrix

This table presents the Pearson correlation matrix between all variables. R is the return of BIST100 index, SENT is the investor sentiment index, IPI is the change in the industrial production index, CPI is the change in the consumer price index, XR is the change in the exchange rate ($/TL), and DUM is the dummy for structural breaks.

	R	SENT	IPI	CPI	XR	DUM
R	1.0000	0.0540	-0.0926	0.1518	-0.0482	0.1104
SENT	0.0540	1.0000	-0.0632	0.3127	0.0891	0.0818
IPI	-0.0926	-0.0632	1.0000	-0.0868	-0.1112	0.0578
CPI	0.1518	0.3127	-0.0868	1.0000	0.4302	0.0698
XR	-0.0482	0.0891	-0.1112	0.4302	1.0000	0.0326
DUM	0.1104	0.0818	0.0578	0.0698	0.0326	1.0000

Third, if the variables are stationary is checked, because the use of non-stationary data may lead to spurious regressions (Brooks, 2014: 354). To detect whether the series involve unit roots, Augmented Dickey-Fuller (ADF) test was performed for each variable. As shown in Table 13, for BIST 100 index return, sentiment index, change in industrial production index, change in exchange rate and the dummy for structural breaks, the test statistics is smaller than the MacKinnon critical values at 1% level. As a result, the null hypothesis of a unit root in the test regression residuals can be rejected, and these variables are stationary at level both with and without trend (I(0)). On the other hand, change in the consumer price index is stationary at the first difference (I(1)). Therefore, the first difference of this variable will be used in the regression analysis.

Table 13. ADF Unit Root Test Results

This table presents the unit root test results of all variables. R_t is the return of BIST100 index, $SENT_{t-1}$ is the investor sentiment index at the preceding month, IPI_t is the change in the industrial production index at month t, CPI_t is the change in the consumer price index at month t, XR_t is the change in the exchange rate ($/TL) at month t, and DUM is the dummy for structural breaks. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

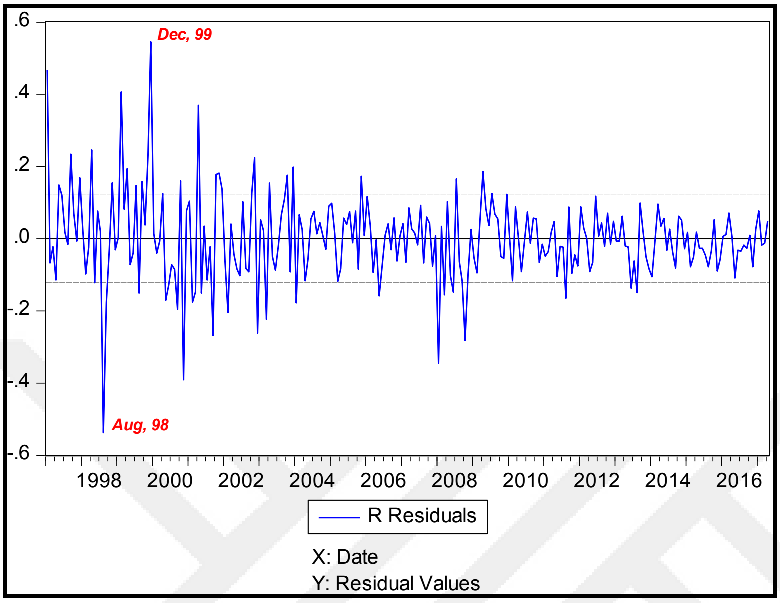
		R_t	$SENT_{t-1}$	IPI_t	CPI_t	XR_t	DUM
Level	**W/O Trend**	-15.94***	-3.18***	-18.22***	-2.25	-6.84***	-16.07***
	W/ Trend	-16.03***	-4.47***	-18.21***	-2.71	-7.12***	-16.16***
1^{st} Diff.	**W/O Trend**	-	-	-	-12.74***	-	-
	W/ Trend	-	-	-	-9.45***	-	-

Fourth, the normality of the residuals was controlled. According to the Jarque-Bera test statistics with the value of 182.011 (statistically significant at %1) null hypothesis of normality was rejected which means residuals are not normally distributed. Brooks (2014: 211) stated that in financial modeling, very extreme residuals, which are called as outliers, may cause rejection of normality and removing those outliers by using dummy variables may improve the model. Figure 4 shows that there are two extreme residual values which were observed in August 1998 and December 1999. Excluding those outliers improve the normality of the distribution of the residuals, and they become close to normality improving the significance of the model.

Finally, serial correlation (autocorrelation) and heteroscedasticity of the series were checked. Serial correlation was analyzed with the Breusch-Godfrey Serial

Correlation LM Test, and according to the results, Prob. Chi Square Value is 0.9686 which is not statistically significant, and therefore it may be stated that there is no autocorrelation problem.

Figure 4. Residuals Graph



Furthermore, heteroscedasticity was analyzed using the White test, and according to the results, Prob. Chi Square Value is 0.0000 which is statistically significant at 1% level, and it indicates heteroscedasticity problem. This result indicates that the series are not homoscedastic, and it means errors do not have a constant variance. This problem may reduce the efficiency of the model, and the coefficients' statistical significance level may decrease. Brooks (2014: 185) suggested that to deal with this problem, an alternative estimation method may be implemented which is called the weighted (or generalized) least squares (WLS). With the WLS model variables in the equation is weighted with the appropriate variable, so the transformed residual's variance become constant (Brooks, 2014: 186). Therefore, to deal with the heteroscedasticity problem, WLS model will be used instead of the ordinary least squares (OLS) model. The weights were identified as the inverse function of the sentiment index (independent variable), and as suggested by Eviews user guide, inverse standard deviation weights with Eviews default scaling was employed, since for other scaling methods (average and none) the non-positive values would be excluded from the analysis.

4.4.2. Regression Results

Following the diagnostic tests and required corrections, the regression equation (17) was tested for the “whole period”, “no crisis period”, “all crisis periods”, “local crisis period”, and “international crisis period” respectively. The whole sample period includes monthly data from January 1997 to November 2017. On the other hand, there are three crises periods, and each of them starts with the pre-crisis date and finishes with the end of the post-crisis date. “No Crisis Period” represents the whole period excluding the crisis dates. “All Crises Periods” includes only the crises periods data. “Local Crisis Period” includes only the data of the 2001 crisis of Turkey. “International Crisis Period” includes both the 1997 Asian and 1998 Russian crises and 2008 Global Financial Crisis data.

As exhibited in Table 14, the included observations vary based on the periods included. According to the F-statistics except the local crisis period, the model is statistically significant and valid at 1% level for each period. In the local crisis period, the significance level drops to the 10% level. The adjusted R-squares range between 4.9% and 32.5 %, which is the reasonable interval according to Cohen (1988: 413-414), and it shows the amount of the total variation in BIST 100 index returns that is explained by the regression model consisting of the preceding month’s sentiment index.

When the coefficients of the independent variable are evaluated, sentiment index is statistically significant and negative for the whole period and no crisis period at the 1% level, and for the local crisis period at the 10% level. In the remaining periods, the coefficient of the sentiment index variable is not found to be statistically significant indicating no statistically significant effect of investor sentiment on BIST 100 index returns. These results could be interpreted as there is no effect of investor sentiment on the stock market in all and global crises periods. Therefore, the effect becomes significant even though it is very small in the periods without crises and in the period with local crisis. Since the whole period includes these two intervals of local crisis and no crisis, the significant effect of investor sentiment is also present for the whole sample.

Table 14. Results of the Regression Analysis

This table presents the results of the regression equation: $R_t = \alpha + \beta_1 SENT_{t-1} + \varepsilon$. The dependent variable is BIST100 index returns, and the independent variable is the preceding month's investor sentiment index ($SENT_{t-1}$). The whole sample period includes monthly data from January 1997 to November 2017. The no crisis period includes monthly data from January 1997 to June 1998, April 1999 to March 2000, April 2004 to September 2007, and May 2010 to November 2017. The all crisis period includes monthly data from August 1998 to January 1999, September 2000 to August 2003, and September 2008 to June 2009. The local crisis period includes monthly data from September 2000 to August 2003. The global crisis period includes monthly data from August 1998 to January 1999, and September 2008 to June 2009. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. t statistics are in the parentheses.

Variables	Whole Period	No Crisis Period	All Crisis Periods	Local Crisis Period	Global Crisis Period
Included Observations	249	161	87	47	39
α	0.077288*** [11.73084]	0.080951*** [11.21721]	0.127117* [1.735602]	0.178075** [2.008844]	-0.073443 [-0.508825]
$SENT_{t-1}$	-0.003497*** [-6.621283]	-0.004394*** [-6.359305]	-0.004112 [-1.503847]	-0.006122* [-1.844602]	0.003265 [0.611820]
Adj. R-Square	0.196967	0.214339	0.168656	0.049637	0.325739
F-statistic	21.27641***	22.82512***	9.723485***	3.402558*	10.17898***

Since, there is a possibility that investor sentiment may be reflecting the effect of economic factors and structural breaks on return; these were included into the analysis as control variables. Thus, the regression analysis was re-done using the regression equation (18) which includes control variables along with the sentiment index variable for each period.

The results of the regression analysis including the macroeconomic variables is presented in Table 15. According to the F-statistics the model is statistically significant and valid for each period. The adjusted R-square values increased ranging between 12.5% to 31.11% showing the amount of the total variation of the index return that is explained by the regression model consisting of the sentiment index, change in the industrial production index, change in the consumer price index (first difference) and change in the exchange rate, and structural breaks as a dummy variable. This increase may be due to the increased number of independent variables.

The coefficients show that the sentiment index is again statistically significant and negatively related with the BIST 100 index returns when the control variables were added to the model in the whole, no crisis and local crisis periods. Therefore, the direction of the relationship and its statistical significance level has not changed even though the value of the coefficient went down with the inclusion of the control variables.

Overall, the results support the hypotheses of the study. Hypothesis one predicted that "there is a significant and negative relationship between investor sentiment and future index returns", hypothesis two predicted that "the effect of investor sentiment is more significant and higher in the whole period relative to the local and international crisis periods", and hypothesis three predicted that "the effect of investor sentiment is more significant and higher in the local crisis periods relative to the international crisis periods". Therefore, the null hypotheses should be rejected for all hypotheses.

Table 15. Results of the Regression Analysis with Control Variables

This table presents the results of the regression equation: $R_t = \alpha + \beta_1 SENT_{t-1} + \beta_2 IPI_t + \beta_3 CPI_t + \beta_4 XR_t + \beta_5 DUM + \varepsilon$. The dependent variable is BIST100 index returns. The independent variables are the preceding month's investor sentiment index (SENT), change in the industrial production index (IPI), first difference of the change in the consumer price index (D(CPI)), change in the exchange rate (XR) and dummy for structural breaks (DUM). The whole sample period includes monthly data from January 1997 to November 2017. The no crisis period includes monthly data from January 1997 to June 1998, April 1999 to March 2000, April 2004 to September 2007, and May 2010 to November 2017. The all crisis period includes monthly data from August 1998 to January 1999, September 2000 to August 2003, and September 2008 to June 2009. The local crisis period includes monthly data from September 2000 to August 2003. The all crisis period includes monthly data from August 1998 to January 1999, and September 2008 to June 2009. The global crisis period includes monthly data from August 1998 to January 1999, and September 2008 to June 2009. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. t statistics are in the parentheses.

Variables	Whole Period	No Crisis Period	All Crises Periods	Local Crisis Period	Global Crisis Period
Included Observations	249	161	87	47	39
α	0.069067*** [7.788593]	0.072476*** [7.102295]	0.132991* [1.686383]	0.179647* [1.853664]	-0.009103 [-0.060187]
$SENT_{t-1}$	-0.002952*** [-5.231999]	-0.003726*** [-4.952558]	-0.004371 [-1.462754]	-0.006102* [-1.646174]	0.001116 [0.199716]
IPI_t	-0.394877* [-1.699086]	-0.333673 [-1.252606]	-0.563122 [-0.975943]	-1.801164** [-2.015934]	0.433451 [0.582709]
$D(CPI_t)$	-1.638331*** [-4.174983]	-1.565509*** [-3.604865]	-0.925967 [-0.706501]	-0.223940 [-0.118335]	-2.309718 [-1.274092]
XR_t	0.044642 [0.313818]	0.039356 [0.228685]	-0.067169 [-0.204216]	0.035517 [0.077951]	-0.355689 [-0.688693]
DUM	-0.016922 [-0.631033]	-0.027385 [-0.929488]	0.138318 [1.394984]	0.190363 [1.437821]	-0.055417 [-0.374668]
Adj. R-Square	0.248226	0.269844	0.168036	0.125165	0.311153
F-statistic	12.69807***	10.85522***	3.894983***	2.316268*	3.860771***

Finally, to provide a support to detect whether the effect of investor sentiment on the BIST 100 index returns differ depending on the existence of the crisis, the additional variable was added to the whole sample regression model as an interaction term. Therefore, the equation (17) is rearranged for the crisis, local crisis and global crisis separately as:

$$R_t = \alpha + \beta_1 SENT_{t-1} + \beta_2 SENT_{t-1} * Crisis + \varepsilon \quad (21)$$

$$R_t = \alpha + \beta_1 SENT_{t-1} + \beta_2 SENT_{t-1} * LocalCrisis + \varepsilon \quad (22)$$

$$R_t = \alpha + \beta_1 SENT_{t-1} + \beta_2 SENT_{t-1} * GlobalCrisis + \varepsilon \quad (23)$$

In equations (21), (22) and (23), the crisis periods were indicated with the dummy variables, where it takes value of 1 during the crisis, local crisis and global crisis, respectively, and it takes the value of 0, otherwise. Each regression equation was also subjected to the analysis by including control variables. The results are presented in Table 16. The results show that the models are statistically significant at 1% level according to the F-statistics, and the adjusted R-square values of each model ranges between 20% to 25%. The coefficients show that investor sentiment is statistically significant and negative for all equations that give support to the initial findings. When the coefficients of interaction terms were evaluated, only the interaction with all crisis ($SENT_{t-1}$*Crisis) is found to be statistically significant and positive. The results have not changed with the inclusion of the control variables as presented in Table 16.

Table 16. Results of the Regression Analysis with Interaction Terms

This table presents the results of the regression equation: $R_t = \alpha + \beta_1 SENT_{t-1} + \beta_2 SENT_{t-1} * Crisis + \varepsilon$, $R_t = \alpha + \beta_1 SENT_{t-1} + \beta_2 SENT_{t-1} * LocalCrisis + \varepsilon$, and $R_t = \alpha + \beta_1 SENT_{t-1} + \beta_2 SENT_{t-1} * GlobalCrisis + \varepsilon$, respectively. The dependent variable is BIST100 index returns, and the independent variable is the preceding month's investor sentiment index ($SENT_{t-1}$) and interaction of the preceding month's investor sentiment index with the crisis ($SENT_{t-1}$*Crisis), with the local crisis ($SENT_{t-1}$*LocalCrisis), and with the global crisis ($SENT_{t-1}$*GlobalCrisis). IPI denotes change in the industrial production index, D(CPI) denotes first difference of the change in the consumer price index, XR denotes change in the exchange rate (XR) and DUM denotes dummy for structural breaks. The whole sample period includes monthly data from January 1997 to November 2017. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. t statistics are in the parentheses.

Variables	Equation (21)		Equation (22)		Equation (23)	
	w/o control variables	w/ control variables	w/o control variables	w/ control variables	w/o control variables	w/ control variables
α	0.081159*** [12.09433]	0.074333*** [8.135215]	0.078906*** [11.85946]	0.071375*** [7.920399]	0.078616*** [11.84716]	0.070704*** [7.895412]
$SENT_{t-1}$	-0.004416*** [-6.864110]	-0.003825*** [-5.527800]	-0.003879*** [-6.663560]	-0.003319*** [-5.319683]	-0.003814*** [-6.692158]	-0.003239*** [-5.318414]
$SENT_{t-1}$ * Crisis	0.002004*** [2.451626]	0.001727*** [2.147508]	-	-	-	-
$SENT_{t-1}$ * LocalCrisis	-	-	0.001508 [1.540921]	0.001303 [1.366319]	-	-
$SENT_{t-1}$ * GlobalCrisis	-	-	-	-	0.001546 [1.460476]	0.001282 [1.242978]
IPI	-	-0.372346* [-1.612434]	-	-0.394821* [-1.701898]	-	-0.378213* [-1.626512]
D(CPI)	-	-1.568452*** [-4.012769]	-	-1.608391*** [-4.099639]	-	-1.615935*** [-4.118216]
XR	-	-4.96E-06 [-3.47E-05]	-	0.025483 [0.178587]	-	0.030362 [0.212982]
DUM	-	-0.016483 [-0.619224]	-	-0.016506 [-0.616577]	-	-0.017006 [-0.634865]
Adj. R-Square	0.213061	0.259327	0.201447	0.250921	0.200664	0.249923
F-statistic	17.78627***	11.85380***	16.64044***	11.38413***	16.56435***	11.32906***

The results indicate that when the crisis periods are included into the analysis the effect of investor sentiment on BIST 100 index returns increases. However, when the crises are separated as local and global, it is found that there is no significant increase in the effect of investor sentiment. Therefore, although it is proven that there is an effect of investor sentiment during the crisis periods, with this result it is not evident that the effect of investor sentiment changes based on the origin of the crisis as local and global. This result contradicts with the initial findings of the study which indicate the effect of investor sentiment is more significant and higher in the local crisis periods relative to the international crisis periods. For that reason, the results need further investigation by including more crisis periods into the analyses.

4.5. ROBUSTNESS TEST: COMPARISON OF THE INVESTOR SENTIMENT INDEX AND OTHER SENTIMENT PROXIES

After detecting the effect of investor sentiment on BIST 100 index returns, it is aimed to compare the performance of each investor sentiment proxy with the constructed sentiment index in the regression analysis to investigate the validity of the index relative to the other proxies. The constructed investor sentiment index was initially composed of six proxies which were closed-end fund discount (CEFD), mutual fund flows (AFLOW), turnover ratio (TURN), share of equity issues in aggregate issues (EQUITY), repo shares in mutual fund portfolios (REPO), and volatility premium (VOLP). Therefore, each one was used in the regression equation (17) and (20) replacing the sentiment index as the sentiment variable and the analysis was re-done.

Before the analysis, if each proxy was stationary was checked since, as mentioned in the previous section, the use of non-stationary data may lead to spurious regressions (Brooks, 2014: 354). As exhibited in Table 17, according to the ADF test results, for $CEFD_{t-1}$, $AFLOW_{t-1}$, $TURN_{t-1}$, $EQUITY_{t-1}$, $REPO_{t-1}$ and $VOLP_{t-1}$ the test statistics are smaller than the MacKinnon critical values at 1% level, so the null hypothesis of a unit root in the test regression residuals can be rejected, and these variables are stationary at level both with and without trend (I(0)).

Table 17. ADF Unit Root Test Results of the Proxies

This table presents the unit root test results of all variables. $CEFD_{t-1}$ is the closed-end fund discount, $AFLOW_{t-1}$ is mutual fund flows, $TURN_{t-1}$ is the turnover ratio, $EQUITY_{t-1}$ is the share of equity issues in aggregate issues, $REPO_{t-1}$ is the repo shares in mutual fund portfolios, and $VOLP_{t-1}$ is the volatility premium, at the preceding month. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

		$CEFD_{t-1}$	$AFLOW_{t-1}$	$TURN_{t-1}$	$EQUITY_{t-1}$	$REPO_{t-1}$	$VOLP_{t-1}$
Level	W/O Trend	-16.36***	-13.13***	-9.54***	-3.59***	-2.54*	-3.77***
	W/ Trend	-16.32***	-13.11***	-9.53***	-11.57***	-3.95***	-3.86***

Finally, the heteroscedasticity and serial correlation of each equations' residuals were checked; because if the problem is detected, to correct it, the weighted least squares (WLS) has to be used as it was done in the previous part. As it is observed in Table 18, according to the Breusch-Godfrey test statistics there is no serial correlation problem in any of the variable series. On the other hand, according to the White test statistics in Table 18, there is a heteroscedasticity problem in the variables except $CEFD_{t-1}$, $AFLOW_{t-1}$ and $TURN_{t-1}$. Therefore, for the $CEFD_{t-1}$, $AFLOW_{t-1}$ and $TURN_{t-1}$ proxies, ordinary lest squares (OLS) method is applied, but for the remaining proxies weighted least squares (WLS) is applied to correct the heteroscedasticity problem[1].

Table 18. Heteroscedasticity and Serial Correlation Test Results

This table presents the White heteroscedasticity test and Breusch-Godfrey serial correlation LM test Prob. Chi-Square values of residuals of each equation. $CEFD_{t-1}$ is the closed-end fund discount, $AFLOW_{t-1}$ is mutual fund flows, $TURN_{t-1}$ is the turnover ratio, $EQUITY_{t-1}$ is the share of equity issues in aggregate issues, $REPO_{t-1}$ is the repo shares in mutual fund portfolios, and $VOLP_{t-1}$ is the volatility premium, at the preceding month. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Variables	White Test	Breusch-Godfrey Serial Correlation LM Test
$CEFD_{t-1}$	0.8629	0.2458
$AFLOW_{t-1}$	0.9167	0.2442
$TURN_{t-1}$	0.3336	0.4066
$EQUITY_{t-1}$	0.0129***	0.2083
$REPO_{t-1}$	0.0000***	0.2690
$VOLP_{t-1}$	0.0041***	0.2629

After the diagnostic tests, the regression analyses were applied to each sentiment proxy, and the results are summarized in Panel A of Table 19. To normalize the residuals, as it is done in the previous section (Figure 4), two extreme residual values which were observed in August 1998 and December 1999 were excluded from the analyses. As exhibited, among the statistically significant models, proxy $REPO_{t-1}$ has the lowest adjusted R-square value with 7.43% and the proxy

[1] Since the observations with zero values cannot be weighted, they are excluded from the analyses.

$TURN_{t-1}$ has the highest value with 18.7%. Overall, the adjusted R-square values of all proxies are lower than the $SENT_{t-1}$ variable (19.6%). Therefore, it could be argued that $SENT_{t-1}$ is more powerful to explain the total variation in BIST 100 index returns in the regression analysis relative to the other proxies.

According to the F-statistics the model is statistically significant and valid at 1% level for each variable except $EQUITY_{t-1}$. Although the significance level of each proxy is the same, when the values are compared with the constructed sentiment index, the F-statistic of $SENT_{t-1}$ is higher than that of other proxies.

When the coefficients are evaluated, sentiment variable is statistically significant and negative for the $TURN_{t-1}$ and $REPO_{t-1}$ proxies, and it is statistically significant and positive for $VOLP_{t-1}$. For the other proxies, the coefficients are positive, but they are not statistically significant, so they do not show any statistically significant effect on BIST 100 index returns. Except $CEFD_{t-1}$, all proxies are a positive indicator of investor sentiment, so similar with $SENT_{t-1}$, a negative relationship is expected between each proxy and the future BIST 100 index returns. On the other hand, for $CEFD_{t-1}$, since it is a negative indicator of investor sentiment, a positive relationship is expected with future BIST 100 index returns.

The findings of the analysis provide supporting evidence to the expected relationship between $CEFD_{t-1}$, $TURN_{t-1}$ and $REPO_{t-1}$ proxies and returns whereas the evidence on the other proxies contradict with the expected relationship. However, as indicated before, the coefficient of $CEFD_{t-1}$ is not statistically significant. Moreover, among the statistically significant proxies, based on the absolute values, the coefficients of $TURN_{t-1}$ and $VOLP_{t-1}$ are slightly higher than the coefficient of $SENT_{t-1}$, while the coefficient of $REPO_{t-1}$ is lower relative to the other proxies.

As previously, the regression analyses were re-done using the regression equation (18) which includes control variables along with the sentiment variable, and the results are summarized in Panel B of Table 19. As exhibited, $CEFD_{t-1}$ equation has the lowest adjusted R-square value with 17.7% and the $EQUITY_{t-1}$ equation has the highest value with 87% which shows the amount of the total variation of index return that is explained by the regression model consisting of the sentiment proxy, change in the industrial production index, in the consumer price index (first difference) and in the exchange rate, and structural breaks as a dummy variable. It is observed that adjusted R-square values has increased with the inclusion of control variables. Brooks (2014: 154) suggested that this value may rise as more variables are added to a model. Furthermore, according to the F-statistics, the model is statistically significant and valid for each proxy.

Coefficients show that the sentiment is statistically significant and positive for the $VOLP_{t-1}$; and statistically significant and negative for the $TURN_{t-1}$ and $REPO_{t-1}$ when the control variables were added to the model. Therefore, the direction of the relationship level has not changed with the inclusion of the control variables. However, the significance level of $REPO_{t-1}$ and $VOLP_{t-1}$ decreased noticeably to the 5% and 10% levels, respectively.

On the other hand, although the significance level of $TURN_{t-1}$ stayed constant, the value of its coefficient went down slightly. Moreover, the significance of the constant term of the regression equation with $VOLP_{t-1}$ proxy has disappeared. Therefore, it could be argued that investor sentiment, proxied by $REPO_{t-1}$ and $VOLP_{t-1}$, is affected by macroeconomic factors and structural breaks, and hence its significance level drops. For the other sentiment proxies, the direction of the relationship and their statistical significance levels have not changed with the inclusion of the control variables, so the effect of investor sentiment proxied by these variables is not affected by economic factors and structural breaks.

Overall, when the proxies are investigated separately, $CEFD_{t-1}$, $AFLOW_{t-1}$ and $EQUITY_{t-1}$ proxies do not have a statistically significant relationship with the BIST 100 index returns when they are subjected to the regression analysis individually. On the other hand, even though $REPO_{t-1}$ and $VOLP_{t-1}$ has a significant relationship with BIST 100 index returns, its effect decreases with the inclusion of the macroeconomic variables and the structural breaks.

Moreover, theoretically, investor sentiment and stock market returns have an inverse relationship with each other. For example, Baker and Wurgler (2006) and Schmeling (2009) argued that when sentiment increases (more optimistic investors), stocks become attractive to optimists and speculators, and they become unattractive to the arbitrageurs, and as a result lower returns are observed during these times. Similarly, in their paper, Bathia and Bredin (2013) found a negative relationship between investor sentiment and stock returns. Therefore, from these theoretical arguments and from the regression results, it could be argued that the composite sentiment index may be a better indicator of investor sentiment relative to the individual proxies.

Among these proxies, only $TURN_{t-1}$ has a strong and negative effect on BIST 100 index return during the indicated period. Although the F-statistic of the composite sentiment index equation is higher than that of the turnover ratio equation, their significance levels are identical, so for the whole period both could be used interchangeably to measure the relationship between investor sentiment and BIST 100 index returns.

Furthermore, the regression analyses were applied to each sentiment proxy for no crisis, all crisis, local crisis and global crisis periods, respectively, both with and without control variables. The results of no crisis period are summarized in Table 20, for both without control variables (Panel A) and with control variables (Panel B). As exhibited, according to the F-statistics, the model is statistically significant and valid for all variables except $EQUITY_{t-1}$. Among the statistically significant models, the adjusted R-square values range between 4.4% ($REPO_{t-1}$) and 31.2% ($TURN_{t-1}$) for the no crisis period.

The coefficients show that sentiment is negative and statistically significant at 1% level for $TURN_{t-1}$, it is negative and statistically significant at 5% level for $REPO_{t-1}$, and it is positive and statistically significant at 1% level for $VOLP_{t-1}$. Although $VOLP_{t-1}$ has the highest coefficient among $SENT_{t-1}$, $TURN_{t-1}$ and $EQUITY_{t-1}$; it contradicts with the investor sentiment theory that predicts negative relationship between sentiment and market return.

When the control variables are added to the models, the adjusted R-square values of all regression equations increased noticeably as was the case for the whole period. The adjusted R-square values range between 27.4% ($AFLOW_{t-1}$) and 87.3% ($EQUITY_{t-1}$). Moreover, according to the F-statistics the model with $EQUITY_{t-1}$ became statistically significant when it is compared with Panel A of Table 20.

When the coefficients are evaluated, the sign and significance levels of the $TURN_{t-1}$ and $VOLP_{t-1}$ proxies did not change, but for the $REPO_{t-1}$ proxy the significance level has decreased to 10% level from 5%. Thus, similar with the results of the whole period, the evidence suggests that in the no crisis period the proxies

$SENT_{t-1}$ and $TURN_{t-1}$ can explain the changes in market returns better compared to the other proxies. Since their prediction levels and the signs are identical, both proxies can be used interchangeably to measure investor sentiment during the periods without crisis.

The results of the regression analyses for all crisis periods are presented in Table 21, for regression equations without control variables (Panel A) and with control variable (Panel B). The F-statistics indicate statistical significance for each equation, and the adjusted R-square takes the values between 9.6% ($CEFD_{t-1}$) and 18.4% ($REPO_{t-1}$). When the coefficients are evaluated, except $EQUITY_{t-1}$ and $VOLP_{t-1}$ equations, they are not statistically significant. The coefficient of $EQUITY_{t-1}$ is statistically significant and positive, which again contradicts with the theory. The coefficient of $VOLP_{t-1}$ is statistically significant and negative. When the control variables are added to the analysis, the signs and the significance levels of both variables do not change.

On the other hand, the significance level of $VOLP_{t-1}$ has disappeared when the crises periods are considered separately as local and global, as shown in Table 22 and Table 23, respectively. Therefore, the reason may be technical, not theoretical, that the significance level of $VOLP_{t-1}$ coefficient might increase due to bigger sample size in all crises period.

Table 22 shows the results of the regression analyses for local crisis period, and as exhibited, neither models nor coefficients are statistically significant. Finally, the regression analyses result for global crisis period are exhibited in Table 23 as Panel A (without control variables) and Panel B (with control variables).

According to the F-statistics the model is statistically significant at 5% level for $EQUITY_{t-1}$ proxy, and for the other proxies it is statistically significant at 1% levels. The adjusted R-square values range between 15.3% ($EQUITY_{t-1}$) and 39.5% ($REPO_{t-1}$). The results of the coefficients show that only $EQUITY_{t-1}$ coefficient is positive and statistically significant at 1% level. However, when the control variables are added to the model, although the model's significance level increases to 1% level with respect to the F-statistic, the significance level of the coefficient goes down to the 10% level. Therefore, the investor sentiment, proxied by $EQUITY_{t-1}$, is affected by macroeconomic factors and structural breaks in the global crisis period.

Table 19. Results of the Regression Analyses for Sentiment Proxies (Whole Period)

The Panel A of this table presents the results of the regression equation for the whole period: $R_t = \alpha + \beta_1 SENT_{\ t-1} + \varepsilon$. The dependent variable is BIST100 index returns, and the independent variable is the preceding month's investor sentiment (SENT) proxied by sentiment index ($SENT_{t-1}$), closed-end fund discount ($CEFD_{t-1}$), mutual fund flows ($AFLOW_{t-1}$), turnover ratio ($TURN_{t-1}$), share of equity issues in aggregate issues ($EQUITY_{t-1}$), repo shares in mutual fund portfolios ($REPO_{t-1}$) and volatility premium ($VOLP_{t-1}$), respectively. The Panel B of this table presents the result of the regression equation for the whole period: $R_t = \alpha + \beta_1 SENT_{t-1} + \beta_2 IPI_t + \beta_3 CPI_t + \beta_4 XR_t + \beta_5 DUM + \varepsilon$. The dependent variable is BIST100 index returns. The independent variables are the preceding month's investor sentiment (SENT), change in the industrial production index (IPI), first difference of the change in the consumer price index (D(CPI)), change in the exchange rate (XR) and dummy for structural breaks (DUM). The whole sample period includes monthly data from January 1997 to November 2017. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. t statistics are in the parentheses.

Variables	Included Observations	α	Sentiment Proxy	IPI	D(CPI)	XR	DUM	Adj. R-Square	F-statistic
				Panel A: Without Control Variables					
$SENT_{t-1}$	250	0.077288*** [11.73084]	-0.003497*** [-6.621283]	-	-	-	-	0.196967	21.27641***
$CEFD_{t-1}$	250	0.016459*** [2.403621]	0.000160 [0.208069]	-	-	-	-	0.160145	16.82662***
$AFLOW_{t-1}$	250	0.016358*** [2.386803]	0.000449 [0.304482]	-	-	-	-	0.160314	16.84647***
$TURN_{t-1}$	250	-0.085770*** [3.402730]	-0.005174*** [-2.853952]	-	-	-	-	0.186919	20.08080***
$EQUITY_{t-1}$	243	0.002762 [0.478855]	-1.175676 [-0.137478]	-	-	-	-	-0.012472	0.006313
$REPO_{t-1}$	244	0.042142*** [8.896654]	-0.000873*** [-2.731266]	-	-	-	-	0.074328	7.503981***
$VOLP_{t-1}$	250	-0.100490*** [-20.15661]	0.214384*** [4.774027]	-	-	-	-	0.106745	10.91856***
				Panel B: With Control Variables					
$SENT_{t-1}$	250	0.069067*** [7.788593]	-0.002952*** [-5.231999]	-0.394877* [-1.699086]	-1.638331*** [-4.174983]	0.044642 [0.313818]	-0.016922 [-0.631033]	0.248226	12.69807***
$CEFD_{t-1}$	250	0.020635*** [2.785729]	0.000179 [0.233202]	-0.499822* [-1.807834]	0.371316 [0.626594]	-0.255895 [-1.570794]	0.103752** [2.134218]	0.177126	8.656860***
$AFLOW_{t-1}$	250	0.020528*** [2.771276]	0.000717 [0.488840]	-0.521540* [-1.889961]	0.372197 [0.628598]	-0.251970 [-1.551660]	0.103397** [2.131123]	0.177753	8.689824***
$TURN_{t-1}$	250	0.085809*** [3.291968]	-0.004836*** [-2.604976]	-0.435455 [-1.599702]	0.139814 [0.236740]	-0.282850* [-1.760861]	0.086044* [1.780826]	0.199391	9.859035***
$EQUITY_{t-1}$	243	-0.017479*** [-3.584126]	0.249605 [0.080946]	-0.816916*** [-6.429454]	21.41684*** [34.78936]	-0.799460*** [-8.371585]	-0.175511 [-0.736002]	0.870219	232.8121***
$REPO_{t-1}$	244	0.039753*** [8.233052]	-0.000651** [-2.250494]	0.025913 [0.134527]	3.594735*** [7.989294]	-0.469316*** [-4.139231]	0.087571 [1.155213]	0.269208	13.78799***
$VOLP_{t-1}$	250	0.017543 [1.412162]	0.057366* [1.691804]	1.138541*** [2.752380]	-6.606323*** [-10.21188]	-1.297243*** [-6.293329]	0.034255 [-6.293329]	0.571591	48.46008***

Table 20. Results of the Regression Analyses for Sentiment Proxies (No Crisis Period)

The Panel A of this table presents the results of the regression equation for no crisis period: $R_t = \alpha + \beta_1 SENT_{\ t-1} + \varepsilon$. The dependent variable is BIST100 index returns, and the independent variable is the preceding month's investor sentiment (SENT) proxied by sentiment index ($SENT_{t-1}$), closed-end fund discount ($CEFD_{t-1}$), mutual fund flows ($AFLOW_{t-1}$), turnover ratio ($TURN_{t-1}$), share of equity issues in aggregate issues ($EQUITY_{t-1}$), repo shares in mutual fund portfolios ($REPO_{t-1}$) and volatility premium ($VOLP_{t-1}$), respectively. The Panel B of this table presents the result of the regression equation for no crisis period: $R_t = \alpha + \beta_1 SENT_{t-1} + \beta_2 IPI_t + \beta_3 CPI_t + \beta_4 XR_t + \beta_5 DUM + \varepsilon$. The dependent variable is BIST100 index returns. The independent variables are the preceding month's investor sentiment (SENT), change in the industrial production index (IPI), first difference of the change in the consumer price index (D(CPI)), change in the exchange rate (XR) and dummy for structural breaks (DUM). The no crisis period includes monthly data from January 1997 to June 1998, April 1999 to March 2000, April 2004 to September 2007, and May 2010 to November 2017. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. t statistics are in the parentheses.

Variables	Included Observations	α	Sentiment Proxy	IPI	D(CPI)	XR	DUM	Adj. R-Square	F-statistic
				Panel A: Without Control Variables					
$SENT_{t-1}$	161	0.080951*** [11.21721]	-0.004394*** [-6.359305]	-	-	-	-	0.214339	22.82512***
$CEFD_{t-1}$	162	0.019772*** [3.232870]	-0.000324 [-0.404779]	-	-	-	-	0.242299	26.74237***
$AFLOW_{t-1}$	162	0.019751 [3.202217]	-0.000262 [-0.173409]	-	-	-	-	0.241661	26.65307***
$TURN_{t-1}$	162	0.125816*** [4.675653]	-0.008344*** [-4.042837]	-	-	-	-	0.312219	37.54302***
$EQUITY_{t-1}$	156	0.023466*** [3.826289]	-2.248448 [-0.212343]	-	-	-	-	-0.012773	0.022556
$REPO_{t-1}$	156	0.043424*** [7.658411]	-0.001100** [-2.334951]	-	-	-	-	0.044481	4.607753***
$VOLP_{t-1}$	162	-0.116438*** [-31.17082]	0.268301*** [6.689380]	-	-	-	-	0.269832	30.74864***
				Panel B: With Control Variables					
$SENT_{t-1}$	161	0.072476*** [7.102295]	0.072476*** [-4.952558]	-0.333673 [-1.252606]	-1.565509*** [-3.604865]	0.039356 [0.228685]	0.039356 [-0.929488]	0.039356	10.85522***
$CEFD_{t-1}$	162	0.026605*** [3.969140]	-0.000130 [-0.163080]	-0.307230 [-1.225347]	0.716342 [1.289048]	-0.459011*** [-2.373110]	0.091412** [2.013765]	0.274375	11.14629***
$AFLOW_{t-1}$	162	0.026798*** [3.967183]	-0.000415 [-0.280358]	-0.309684 [-1.234319]	0.727206 [1.316622]	-0.459944*** [-2.378124]	0.092200** [2.046992]	0.274618	11.15869***
$TURN_{t-1}$	162	0.128042*** [4.692583]	-0.007928*** [-3.827192]	-0.300643 [-1.255739]	0.563242 [1.063157]	-0.466690*** [-2.523919]	0.060462 [1.378533]	0.336912	14.63389***
$EQUITY_{t-1}$	156	0.043787*** [5.613213]	-4.749949 [-1.248447]	-2.441577*** [-11.89850]	9.641199*** [7.249363]	0.0743386 [0.580440]	-0.088569 [-0.381029]	0.873812	179.8883***
$REPO_{t-1}$	156	0.039560*** [7.109944]	-0.000758* [-1.821634]	0.094989 [0.434314]	3.872857*** [7.562199]	-0.488037*** [-3.762594]	0.053787 [0.544708]	0.300758	12.11143***
$VOLP_{t-1}$	162	-0.131782*** [-4.016430]	0.210256*** [4.885690]	0.438946 [0.994822]	-4.629350*** [-8.442806]	1.299753** [1.972904]	0.025434 [0.714903]	0.522826	30.40055***

Table 21. Results of the Regression Analyses for Sentiment Proxies (All Crisis Periods)

The Panel A of this table presents the results of the regression equation for all crisis period: $R_t = \alpha + \beta_1 SENT_{t-1} + \varepsilon$. The dependent variable is BIST100 index returns, and the independent variable is the preceding month's investor sentiment (SENT) proxied by sentiment index ($SENT_{t-1}$), closed-end fund discount ($CEFD_{t-1}$), mutual fund flows ($AFLOW_{t-1}$), turnover ratio ($TURN_{t-1}$), share of equity issues in aggregate issues ($EQUITY_{t-1}$), repo shares in mutual fund portfolios ($REPO_{t-1}$) and volatility premium ($VOLP_{t-1}$), respectively. The Panel B of this table presents the result of the regression equation for all crisis period: $R_t = \alpha + \beta_1 SENT_{t-1} + \beta_2 IPI_t + \beta_3 CPI_t + \beta_4 XR_t + \beta_5 DUM + \varepsilon$. The dependent variable is BIST100 index returns. The independent variables are the preceding month's investor sentiment (SENT), change in the industrial production index (IPI), first difference of the change in the consumer price index (D(CPI)), change in the exchange rate (XR) and dummy for structural breaks (DUM). The all crisis period includes monthly data from August 1998 to January 1999, September 2000 to August 2003, and September 2008 to June 2009. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. t statistics are in the parentheses.

Variables	**Included Observations**	**α**	**Sentiment Proxy**	**IPI**	**D(CPI)**	**XR**	**DUM**	**Adj. R-Square**	**F-statistic**
				Panel A: Without Control Variables					
$SENT_{t-1}$	87	0.127117* [1.735602]	-0.004112 [-1.503847]	-	-	-	-	0.168656	9.723485***
$CEFD_{t-1}$	87	0.010078 [0.618348]	-5.61E-05 [-0.037559]	-	-	-	-	0.096078	5.570460***
$AFLOW_{t-1}$	87	0.010634 [0.653193]	0.000968 [0.331704]	-	-	-	-	0.097245	5.631970***
$TURN_{t-1}$	87	0.046327 [0.884795]	-0.002472 [-0.726718]	-	-	-	-	0.101710	5.868738***
$EQUITY_{t-1}$	86	-0.137862*** [-382.9157]	1.441042*** [4.483148]	-	-	-	-	0.175667	10.05685***
$REPO_{t-1}$	87	0.059953 [1.047305]	-0.000898 [-0.805317]	-	-	-	-	0.184231	10.71098***
$VOLP_{t-1}$	87	0.092608*** [7.539495]	-0.156124*** [-2.985011]	-	-	-	-	0.146627	8.388301***
				Panel B: With Control Variables					
$SENT_{t-1}$	87	0.132991* [1.686383]	-0.004371 [-1.462754]	-0.563122 [-0.975943]	-0.925967 [-0.706501]	-0.067169 [-0.204216]	0.138318 [1.394984]	0.168036	3.894983***
$CEFD_{t-1}$	87	0.010023 [0.568510]	-0.000443 [-0.282413]	-0.808607 [-1.214730]	-0.103598 [-0.082331]	-0.122477 [-0.390670]	0.131177 [1.202474]	0.085931	2.347467**
$AFLOW_{t-1}$	87	0.012302 [0.697360]	0.002167 [0.702142]	-0.916400 [-1.343473]	-0.069021 [-0.054949]	-0.149468 [-0.478992]	0.128980 [1.185913]	0.090624	2.428386**
$TURN_{t-1}$	87	0.037775 [0.666306]	-0.001839 [-0.504131]	-0.705956 [-1.066793]	-0.210081 [-0.165439]	-0.149333 [-0.476427]	0.124574 [1.138009]	0.087917	2.381615**
$EQUITY_{t-1}$	86	-0.044311*** [-3.711737]	0.764298*** [3.168106]	-2.098967*** [-3.771603]	2.339602 [1.566119]	-2.302623*** [-9.221818]	-0.251824 [-0.295539]	0.591310	21.49697***
$REPO_{t-1}$	87	0.073334 [1.123537]	-0.001122 [-0.867471]	-1.078783* [-1.717020]	-0.821726 [-0.627805]	-0.154758 [-0.414848]	0.138248 [1.286471]	0.198194	4.542967***
$VOLP_{t-1}$	87	0.090362*** [4.707544]	-0.172539*** [-2.882746]	1.168372* [1.776515]	-4.731273*** [-3.354223]	0.387504 [1.280646]	0.129652 [0.619631]	0.227818	5.228793***

Table 22. Results of the Regression Analyses for Sentiment Proxies (Local Crisis Period)

The Panel A of this table presents the results of the regression equation for local crisis period: $R_t = \alpha + \beta_1 SENT_{t-1} + \varepsilon$. The dependent variable is BIST100 index returns, and the independent variable is the preceding month's investor sentiment (SENT) proxied by sentiment index ($SENT_{t-1}$), closed-end fund discount ($CEFD_{t-1}$), mutual fund flows ($AFLOW_{t-1}$), turnover ratio ($TURN_{t-1}$), share of equity issues in aggregate issues ($EQUITY_{t-1}$), repo shares in mutual fund portfolios ($REPO_{t-1}$) and volatility premium ($VOLP_{t-1}$), respectively. The Panel B of this table presents the result of the regression equation for local crisis period: $R_t = \alpha + \beta_1 SENT_{t-1} + \beta_2 IPI_t + \beta_3 CPI_t + \beta_4 XR_t + \beta_5 DUM + \varepsilon$. The dependent variable is BIST100 index returns. The independent variables are the preceding month's investor sentiment (SENT), change in the industrial production index (IPI), first difference of the change in the consumer price index (D(CPI)), change in the exchange rate (XR) and dummy for structural breaks (DUM). The local crisis period includes monthly data from September 2000 to August 2003. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. t statistics are in the parentheses.

Variables	Included Observations	α	Sentiment Proxy	IPI	D(CPI)	XR	DUM	Adj. R-Square	F-statistic
				Panel A: Without Control Variables					
$SENT_{t-1}$	47	0.178075** [2.008844]	-0.006122* [-1.844602]	-	-	-	-	0.049637	3.402558*
$CEFD_{t-1}$	47	0.000567 [0.023538]	-0.000545 [-0.278207]	-	-	-	-	-0.020467	0.077399
$AFLOW_{t-1}$	47	0.002956 [0.123135]	-0.039847 [-0.754705]	-	-	-	-	-0.009445	0.569579
$TURN_{t-1}$	47	0.079220 [1.097479]	-0.004983 [-1.146172]	-	-	-	-	0.006774	1.313709
$EQUITY_{t-1}$	47	0.045191*** [2.576350]	-0.114861 [-0.452256]	-	-	-	-	-0.017597	0.204535
$REPO_{t-1}$	47	0.065727 [0.948530]	-0.001178 [-0.833472]	-	-	-	-	-0.006682	0.694676
$VOLP_{t-1}$	47	0.030510 [1.039280]	-0.089553 [-1.162000]	-	-	-	-	0.007556	1.350244
				Panel B: With Control Variables					
$SENT_{t-1}$	47	0.179647* [1.853664]	-0.006102* [-1.646174]	-1.801164** [-2.015934]	-0.223940 [-0.118335]	0.035517 [0.077951]	0.190363 [1.437821]	0.125165	2.316268*
$CEFD_{t-1}$	47	0.005806 [0.226465]	-0.001767 [-0.888314]	-2.034836** [-2.070504]	0.907163 [0.532897]	-0.131807 [-0.320113]	0.208363 [1.273935]	0.057469	1.560950
$AFLOW_{t-1}$	47	0.007718 [0.299333]	-0.023045 [-0.433658]	-1.798805* [-1.851082]	0.655833 [0.372952]	-0.147606 [-0.355019]	0.213094 [1.293730]	0.043715	1.420561
$TURN_{t-1}$	47	0.049671 [0.654126]	-0.002708 [-0.592797]	-1.744668* [-1.782619]	0.618874 [0.354556]	-0.184011 [-0.446358]	0.209018 [1.271023]	0.047492	1.458715
$EQUITY_{t-1}$	47	0.079698*** [5.273309]	-0.057824 [-0.303772]	-4.380300*** [-6.177122]	0.515146 [0.262437]	-1.545815*** [-3.946988]	0.077488 [0.144409]	0.500269	10.20992***
$REPO_{t-1}$	47	0.118411 [1.550301]	-0.002015 [-1.280657]	-2.350708*** [-2.499716]	0.044700 [0.024035]	-0.027755 [-0.054196]	0.194856 [1.294491]	0.107484	2.107943*
$VOLP_{t-1}$	47	0.042365 [1.432976]	-0.110082 [-1.402746]	-1.769200* [-1.726500]	-1.234687 [-0.463165]	0.375366 [0.628699]	0.259059 [0.988914]	0.033198	1.315905

Table 23. Results of the Regression Analyses for Sentiment Proxies (Global Crisis Periods)

The Panel A of this table presents the results of the regression equation for global crisis periods: $R_t = \alpha + \beta_1 SENT_{t-1} + \varepsilon$. The dependent variable is BIST100 index returns, and the independent variable is the preceding month's investor sentiment (SENT) proxied by sentiment index ($SENT_{t-1}$), closed-end fund discount ($CEFD_{t-1}$), mutual fund flows ($AFLOW_{t-1}$), turnover ratio ($TURN_{t-1}$), share of equity issues in aggregate issues ($EQUITY_{t-1}$), repo shares in mutual fund portfolios ($REPO_{t-1}$) and volatility premium ($VOLP_{t-1}$), respectively. The Panel B of this table presents the result of the regression equation for global crisis period: $R_t = \alpha + \beta_1 SENT_{t-1} + \beta_2 IPI_t + \beta_3 CPI_t + \beta_4 XR_t + \beta_5 DUM + \varepsilon$. The dependent variable is BIST100 index returns. The independent variables are the preceding month's investor sentiment (SENT), change in the industrial production index (IPI), first difference of the change in the consumer price index (D(CPI)), change in the exchange rate (XR) and dummy for structural breaks (DUM). The no crisis period includes monthly data from January 1997 to June 1998, April 1999 to March 2000, April 2004 to September 2007, and May 2010 to November 2017. The global crisis period includes monthly data from August 1998 to January 1999, and September 2008 to June 2009. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. t statistics are in the parentheses.

Variables	Included Observations	α	Sentiment Proxy	IPI	D(CPI)	XR	DUM	Adj. R-Square	F-statistic
Panel A: Without Control Variables									
$SENT_{t-1}$	39	-0.073443 [-0.508525]	0.003265 [0.611820]	-	-	-	-	0.325739	10.17898***
$CEFD_{t-1}$	39	0.018968 [0.880802]	0.002336 [0.970324]	-	-	-	-	0.263347	7.792331***
$AFLOW_{t-1}$	39	0.018217 [0.833773]	0.001252 [0.479768]	-	-	-	-	0.248883	7.295671***
$TURN_{t-1}$	39	-0.098296 [-0.997298]	0.008779 [1.194751]	-	-	-	-	0.272911	8.131584***
$EQUITY_{t-1}$	38	-0.137905*** [-336.8108]	1.631676*** [2.945187]	-	-	-	-	0.153046	4.342988**
$REPO_{t-1}$	39	-0.048093 [-0.206126]	0.001140 [0.274955]	-	-	-	-	0.395764	13.44469***
$VOLP_{t-1}$	39	0.098912*** [6.840425]	-0.132586 [-1.613093]	-	-	-	-	0.164405	4.738278***
Panel B: With Control Variables									
$SENT_{t-1}$	39	-0.009103 [-0.060187]	0.001116 [0.199716]	0.433451 [0.582709]	-2.309718 [-1.274092]	-0.355689 [-0.688693]	-0.055417 [-0.374668]	0.311153	3.860771***
$CEFD_{t-1}$	39	0.026156 [1.161997]	0.003289 [1.359397]	0.861144 [1.002223]	-2.942194 [-1.591791]	-0.425955 [-0.840513]	-0.085880 [-0.624927]	0.293671	3.633213***
$AFLOW_{t-1}$	39	0.020783 [0.899235]	-0.000342 [-0.116445]	0.768686 [0.782577]	-2.952542 [-1.530858]	-0.328186 [-0.631959]	-0.071799 [-0.507547]	0.253198	3.147268***
$TURN_{t-1}$	39	-0.041005 [-0.375412]	0.004687 [0.582203]	0.553023 [0.603244]	-2.731035 [-1.424730]	-0.314682 [-0.611028]	-0.051636 [-0.359361]	0.260712	3.233469***
$EQUITY_{t-1}$	38	-0.065572*** [-3.759437]	0.818756* [1.732649]	-1.392813 [-1.351243]	-0.525280 [-0.167671]	-1.986444*** [-4.823262]	-0.442594 [-0.252894]	0.479110	6.672042***
$REPO_{t-1}$	39	-0.023680 [-0.091480]	0.000807 [0.173998]	0.624967 [0.738267]	-2.945276 [-1.533052]	-0.423461 [-0.787451]	-0.073428 [-0.494325]	0.410977	5.418938***
$VOLP_{t-1}$	39	0.061305 [2.753742]	-0.104129 [-1.232518]	3.622803*** [4.015014]	-8.785711*** [-4.918251]	0.885100*** [2.513274]	-0.205744 [-0.746193]	0.486401	6.997944***

So, comprehensively, although composite sentiment index and turnover rate could be used interchangeably based on the results for whole and no crisis periods, the significance level of turnover rate has disappeared for the crisis periods while the composite sentiment index is still statistically significant for the local crisis period.

Moreover, although each proxy is regarded to reflect the same investor sentiment; their results for identical periods are very different. As summarized in Table 24, while investor sentiment index (SENT) is statistically significant and negative in the whole, no crisis and local crisis periods, closed-end fund discount (CEFD) and mutual fund flows (AFLOW) are not statistically significant in none of the periods. On the other hand, turnover rate (TURN) and repo shares in mutual fund portfolios (REPO) are statistically significant and negative only in the whole and no crisis periods. Controversially, the share of equity issues in aggregate issues (EQUITY) is statistically significant and positive in the all crisis and global crisis periods which is inconsistent with the theory. Similarly, while volatility premium (VOLP) is statistically significant and positive in the whole and no crisis periods, it is statistically significant and negative in the all crisis period.

Table 24. Summary of the Results of the Proxies

This table presents the summary of the results of each proxy. (−) represents statistically significant and negative relationship, (+) represents statistically significant and positive relationship, (x) represents no statistically significant relationship between investor sentiment and BIST 100 index returns. SENT is the investor sentiment index, CEFD is the closed-end fund discount, AFLOW is the mutual fund flows, TURN is the turnover ratio, EQUITY is the share of equity issues in aggregate issues, REPO is the repo shares in mutual fund portfolios, and VOLP is the volatility premium.

Proxy	Expected Relationship	Whole Period	No Crisis Period	All Crisis Period	Local Crisis Period	Global Crisis Period
SENT	−	−	−	x	−	x
CEFD	+	x	x	x	x	x
AFLOW	−	x	x	x	x	x
TURN	−	−	−	x	x	x
EQUITY	−	x	x	+	x	+
REPO	−	−	−	x	x	x
VOLP	−	+	+	−	x	x

Therefore, the results give support to the discussion of Baker and Wurgler (2006) that combining these separate proxies may increase the validity of the proxy reflecting investor sentiment and its relationship with the stock market. Therefore, market-based proxies are influenced by the crises in a different way, and the composite sentiment index is able to combine their conflicting reactions to the crises.

CONCLUSION

Behavioral finance is a specialized field of finance which relieves the rationality assumption of classical finance theories and instead of disregarding psychological factors; behavioral finance researchers consider these factors as an additional source of systematic risk in the market. Within this context, investor sentiment has played a significant role in the behavioral finance research, which is defined basically as the general feelings of optimism and pessimism level of investors about the market. When the literature on investor sentiment is scrutinized, it is observed that investor sentiment is influential on stock markets, and the relationship between investor sentiment and future stock returns is generally found to be significantly negative not only for the developed markets such as the U.S. and European markets but also for the developing markets such as Turkey and China.

Additionally, it is argued that collective optimism and pessimism levels of investors may lead to economic crisis, and only a few studies analyzed the effect of investor sentiment on stock markets during the economic crisis periods (Baur, Quintero and Stevens, 1998; Bolaman and Mandacı, 2014; Zouaoui, et al., 2011), even though the stock markets may be under the effect of investor sentiment during these periods. Alongside these empirical evidences, since sentiment cannot be observed directly in the market, the rest of the literature generally focused on finding the most proper proxy for investor sentiment. Beside survey-based direct measurements such as American Association of Individual Investors (AAII) Sentiment Survey, Investors Intelligence (II) Index, etc., and market-based indirect measurements such as closed-end fund discounts, mutual fund flows, etc., some researchers combined several proxies to form a composite sentiment index such as Baker and Wurgler (2006) sentiment index.

In light of the above explanations, there are four main contributions of this study. To the best of the author’s knowledge, none of the studies investigated power and sign of the effect of investor sentiment on the stock market returns during the crisis periods. Therefore, the first contribution and the main aim of this study is to analyze the impact of investor sentiment on Borsa Istanbul as a developing market during the crisis periods beginning from 1997 to 2017.

However, before investigating the probable effects of investor sentiment on stock returns, it was crucial to select the appropriate investor sentiment proxy for Borsa Istanbul. In Turkey, Kaya (2017) and Keleş, et al. (2017) constructed a sentiment index, but Kaya (2017) used annual data, and Keleş et al. (2017) included observations beginning from 2005 and they tested the effect of sentiment on energy prices. Thus, the second contribution is made by constructing a new and an appropriate composite sentiment index for Borsa Istanbul with the monthly data beginning from 1997 to 2017.

Further, the detected crises were separated as local and international based on their origin to analyze if the pattern of investor sentiment differs between locally and internationally originating crises, which is the third contribution of this study.

The last contribution of the study is to eliminate the possible effects of macroeconomic variables along with the structural breaks which were detected by Carrion-i-Silvestre et al. (2009) unit root test, and these variables were added as a control variable to the model.

Overall, three hypotheses were determined as “H1: There is a significant and negative relationship between investor sentiment future index returns”, “H2: The effect of investor sentiment is more significant and higher in the whole period relative to the local and international crisis periods”, and “H3: The effect of investor sentiment is more significant and remarkable in the local crisis periods relative to the other periods”.

Within the scope of the aim and hypotheses, first, investor sentiment index was constructed which is applicable to Turkey. Based on the literature and data availability; six proxies were selected. These are; closed-end fund discount, mutual fund flows, turnover ratio, share of equity issues in aggregate issues, repo shares in mutual fund portfolios, and volatility premium. The monthly data used covers the period between 1997-2017. To form an investor sentiment index, in this study Baker and Wurgler (2006) procedure was followed, and principal component of the six proxies were taken into consideration. Since the KMO value was not factorable, the volatility premium needed to be removed from the principal component analysis to raise the value of KMO. Therefore, the final composite sentiment index was composed of closed-end fund discount, mutual fund flows, turnover ratio, share of equity issues in aggregate issues and repo shares in mutual fund portfolios which was later used to investigate the effect of investor sentiment in the crisis periods for the Turkish stock market.

Second, the CMAX crisis indicator, which was firstly introduced by Patel and Sarkar (1998), was used to detect the crisis periods in Turkey, and the detected crises were separated as local and international; to analyze if the pattern of investor sentiment differs between the crises based on their origin being local or international. Over the period between 1997 and 2017, three crises were detected. Among them, the period from September 2000 to August 2003 corresponds with the 2001 Turkish financial crisis which can be categorized as local. Other two crisis periods correspond with the 1997 Asian and 1998 Russian financial crises (the period from August 1998 to January 1999), and 2008 global financial crisis (the period from September 2008 to June 2009), respectively. All these crises can be categorized as international crises.

Third, the regression analysis was conducted to investigate the effect of investor sentiment on the future stock market returns during the determined crisis periods. Since, there is a possibility that investor sentiment can be affected by economic factors; chosen factors were included into the analysis as control variables at the later stage. The determined economic control variables, which were selected based on the related literature, are the change in the industrial production index, consumer price index and the change in the exchange rate ($). Besides these macroeconomic control variables, structural breaks during the indicated period are also used as control variables and they are included in the regression equation as a dummy variable. Five structural breaks were determined (August 1997, November 1999, November 2002, December 2007 and July 2011) based on the Carrion-i-Silvestre, et al. (2009) unit root test, and these are mostly clustered around the important economic and political events such as the 1997 Asian and 1998 Russian financial crises, November 1999 Düzce Earthquake, 2001 Turkish financial crisis, 2008 global financial crisis and 2011 European debt crisis.

The regression equations were tested for the whole period and the crisis periods separately using Eviews software program. To observe the impact of each crisis period; “whole period”, “no crisis period”, “all crisis periods”, “local crisis period" and "international crisis periods" were subjected to the same regression analyses. The results showed that investor sentiment is statistically significant and negatively related with the future BIST 100 index returns in the whole, no crisis and local crisis periods, and neither the statistical significance nor the coefficient of the sentiment changed with the inclusion of the control variables. Based on the results, the effect of investor sentiment is more significant and higher in the whole period relative to the local and international crisis periods, and it is more significant and higher in the local crisis period relative to the international crisis period. These results support all hypotheses of the study.

Further, to detect whether the effect of investor sentiment on the BIST 100 index returns differ depending on the existence of the crisis, the additional variable was added to the whole sample regression model as an interaction term. The results indicate that when the crisis periods included into the analysis the effect of investor sentiment on BIST 100 index returns increases. However, when the crises are separated as local and global, it is found that there is no significant increase in the effect of investor sentiment. Therefore, although it is proven that there is an effect of investor sentiment during the crisis periods, with this result it is not evident that the effect of investor sentiment changes based on the origin of the crisis as local and global. This result contradicts with the initial findings of the study which indicate the effect of investor sentiment is more significant and higher in the local crisis periods relative to the international crisis periods.

In general, for the whole period the results show that when investors are more optimistic (pessimistic), future stock market returns tend to decrease (increase). The result is consistent with the investor sentiment theory that supports inverse relationship between investor sentiment and future stock market returns. For example, Brown and Cliff (2004b: 405) argue that overly optimistic investors force prices to increase above their intrinsic values, and since prices revert to intrinsic values the overpriced securities tend to be followed by low returns. Moreover, Baker and Wurgler (2006) and Schmeling (2009) argue that when sentiment increases (more optimistic investors), stocks become attractive to optimists and speculators, and they become unattractive to the arbitrageurs, and as a result lower returns are observed during these times. Similarly, in their paper, Bathia and Bredin (2013) found a negative relationship between investor sentiment and stock returns.

Furthermore, the results remain constant for the period without crises and for the period with the 2001 Turkish financial crisis. However, when the analyses are done for the international financial crisis periods, namely 1997 Asian and 1998 Russian financial crises, and 2008 global financial crisis, the statistical significance of the investor sentiment coefficient disappeared. Therefore, it cannot be argued that investor sentiment is affective on stock market returns during these times. The result is consistent with the findings of Ergün and Durukan (2017) who found a significant effect of investor sentiment only during the local crisis period by using closed-end fund discount as a proxy for investor sentiment. However, it contradicts with the findings of Bolaman and Mandacı (2014) who found long-run relationship between investor sentiment (proxied by consumer confidence index) and stock market in the presence of 2008 global financial crisis. The conflicting evidence may be due to differences in methods, periods and proxies used.

Based on the Central Securities Depository (CSD) of Turkey, currently in Borsa Istanbul the share of foreign investors is approximately 63%, so their influence on stock market is substantial. Similar with Ergün and Durukan (2017), the results could be interpreted as since during the international financial crisis all markets are affected from the crises, international investors may not leave their current investments, and for the purpose of diversifying their portfolios internationally, they may continue trading at Borsa Istanbul. As a result, the pessimism level of those investors may not significantly affect the overall market during the international crisis periods. However, the local crisis affects only Borsa Istanbul, hence foreign investors may desire to invest their funds in other alternative markets which are not affected from the crisis, so this time, their pessimism level may have an impact on stock market returns.

On the other hand, the results may be interpreted with the rational component of the sentiment. As discussed in the first chapter, not all sentiment is due to noise, it may also be caused by fundamentals such as public announcements of dividends (Shleifer and Summers, 1990: 23). In this study the rational and irrational components of the sentiment were not separated, however if it is assumed that the irrational component is more dominant in the composite sentiment index, it may be argued that during the international crises investors act based on the fundamentals rather than the noise or their sentiment, so the effect of their pessimism level is not significant during these times.

For the last step, after detecting the effect of investor sentiment on BIST 100 index returns, it was aimed to compare the performance of each investor sentiment proxy with the constructed sentiment index in the regression analysis to investigate the validity of the constructed index relative to the other proxies. Based on the results, for the whole and no crisis periods, closed-end fund discount, mutual fund flows and share of equity issues in aggregate issues were found to be not statistically significant. On the other hand, repo shares in mutual fund flows and volatility premium were found to be positive and statistically significant, however besides their contradiction with the theory (the influence has to be negative), their influence decreased with the inclusion of macroeconomic variables and structural breaks, so these variables are affected from the mentioned control variables. Only turnover ratio had a strong and negative effect in the whole and no crisis periods.

When the remaining periods are evaluated, in the local crisis period none of the proxies were statistically significant. In the all and global crisis periods, share of equity issues in aggregate issues was found to be statistically significant and positive which again contradicts with the investor sentiment theory. Moreover, in the all crisis period, volatility premium was significantly negative, but its significance level has disappeared when the crisis periods were divided as local and international. Therefore, the reason may be technical, not theoretical, that since the sample size increases in all crisis period, the significance level of volatility premium coefficient might also increase.

Although the absence of statistical significance of the proxies is not a proof for being an inappropriate measurement of investor sentiment, according to the previous studies the effect of investor sentiment is distinctive in both developed and developing countries' stock market. For that reason, a composite sentiment index and turnover rate could be used interchangeably based on the results for whole and no crisis periods. However, the significance level of turnover rate has disappeared for the crisis periods while composite sentiment index is still statistically significant on the local crisis period.

Moreover, although each proxy is assumed to measure the same investor sentiment; their results for the identical periods are very different. For example, while investor sentiment index is statistically significant and negative in the whole, no crisis and local crisis periods, closed-end fund discount and mutual fund flows are not statistically significant in none of the periods. On the other hand, turnover rate and repo shares in mutual fund portfolios are statistically significant and negative only in the whole and no crisis periods. Controversially, the share of equity issues in aggregate issues is statistically significant and positive in the all crisis and global crisis periods which is inconsistent with the theory. Similarly, while volatility premium is statistically significant and positive in the whole and no crisis periods, it is statistically significant and negative in the all crisis period. Thus, the results give support to the discussion of Baker and Wurgler (2006) that combining these separate proxies may increase the power of the investor sentiment proxy in estimating stock returns. Furthermore, market-based proxies show reaction to the crises in a different way, and composite sentiment index is able to combine their conflicting reactions to the crises.

Consequently, although confidence indices are survey-based proxies for investor sentiment there is no comprehensive and direct investor sentiment survey like American Association of Individual Investors (AAII) Sentiment Survey in Turkey, so this deficiency prevents comparing the aforementioned proxies with the sentiment surveys and it is one of the major limitations of this study. However, for the further studies, each proxy and composite sentiment index may be compared with the consumer confidence index or economic sentiment indicator to investigate their validity. The second limitation of the study is that the results contradicted with the initial findings when the interaction term of investor sentiment and crisis periods were added to the model. For that reason, the results need further investigation by including more crisis periods into the analyses. The third limitation of the study is the lack of daily data (among the selected proxies only trading volume has daily frequency data). In the crisis periods, daily frequency data may capture the effect of sentiment better. Therefore, as a further study only turnover ratio may be used, and the analyses could be done on a daily basis to test and compare the effect of investor sentiment during crisis periods. The last limitation is that in this study the rational and the irrational component of investor sentiment were not separated. Therefore, taking these separately into consideration will be a worthwhile contribution for further studies.

To sum up, the findings show that Borsa Istanbul is sensitive to investor sentiment particularly in the crisis periods, more in local crisis periods than global crisis. For that reason, the presence of investor sentiment should be considered while taking important investment decisions on these risky periods. Moreover, policy makers and domestic and foreign investors shall consider investor sentiment as an additional source of systematic risk while formulating their asset pricing models. Finally, policy makers shall also take account of the effect of investor sentiment in the market when formulating policies especially during local crises.

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