ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

THE EFFECTS OF INVESTOR SENTIMENT ON CONDITIONAL VOLATILITY OF ASSET RETURNS: EVIDENCE FROM INTERNATIONAL STOCK MARKETS

Ph.D. THESIS

Utku UYGUR

Department of Management Engineering

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

YATIRIMCI DUYARLILIĞININ VARLIK GETİRİLERİNİN KOŞULLU DEĞİŞKENLİĞİNE ETKİSİ: ULUSLARARASI BORSALARDAN ÖRNEKLER

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OCAK 2015

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Date of Submission : 13 November 2014
Date of Defense : 9 January 2015

To my dearest beloved,

FOREWORD

The main purpose of this thesis is to provide a simple framework to evaluate the various effects of the investor sentiment on the conditional volatility in stock markets. Although there is considerable amount of previous work dedicated to investor sentiment, this thesis aims to provide better insight and understanding by exploring the effects on both individual stock and economical sector basis.

I would like to thank Prof. Oktay Taş for his advice and encouragement throughout this project, as well as Prof. Burç Ülengin and Prof. Suat Teker for their expertise and their recommendations.

January 2015 Utku UYGUR

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ABBREVIATIONS

AAII : The American Association of Individual Investors
ARCH : Autoregressive Conditional Heteroskedasticity
ARMA : Autoregressive Moving Average
BIST : Borsa Istanbul
BSI : Buy-Sell Imbalance
CAC 40 : Cotation Assistee en Continu
CEF : Closed-end Fund
CEFD : Closed-end Fund Discount
DAX 30 : Deutscher Aktienindex
DJIA : Dow Jones Industrial Average
DSSW : De Long, Shleifer, Summers, and Waldmann
EGARCH : Exponential Generalized Autoregressive Conditional Heteroskedasticity
EGARCH-M : Exponential Generalized Autoregressive Conditional Heteroskedasticity in Mean
EGB_2 : Exponential Generalized Beta Distribution
EMH : Efficient Market Hypothesis
FTSE 100 : Financial Times Stock Exchange
GARCH : Generalized Autoregressive Conditional Heteroskedasticity
GARCH-M : Generalized Autoregressive Conditional Heteroskedasticity in Mean
GJR-GARCH: Glosten, Jagannathan, and Runkle Generalized Autoregressive Conditional Heteroskedasticity
HML : High minus Low
HSI : Hang Seng Index
IPO : Initial Public Offering
ISE : Istanbul Stock Exchange
NASDAQ : National Association of Securities Dealers Automated Quotations
NBER : National Bureau of Economic Research
NIKKEI : Nihon Keizai Shimbun
NIS : Net Investor Sentiment
NYSE : New York Stock Exchange
S&P 500 : Standard and Poor's 500 Composite Index
SMB : Small minus Big
SWARCH : Switch Autoregressive Conditional Heteroskedasticity
TED : Treasury Bill Eurodollar
VAR : Value At Risk
VIX : Chicago Board Options Exchange Market Volatility Index

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THE EFFECTS OF INVESTOR SENTIMENT ON CONDITIONAL VOLATILITY OF ASSET RETURNS: EVIDENCE FROM INTERNATIONAL STOCK MARKETS

SUMMARY

Noise trader theory states that stock prices are determined by the interaction of rational arbitrageurs and noise traders in addition to standard risk factors and macroeconomic variables making room for the presence of investor sentiment. Noise traders, who are naive and inexperienced, are likely to have a poor judgment of how to measure risk and as a result likely to miscalculate the variance of returns which undermines the mean-variance relation. Empirical evidence also suggests that they participate and trade more aggressively in high-sentiment periods.

Although the increasing participation of noise traders in the market provides additional liquidity, it would also mean additional noise trader risk, hence volatility. Moreover, considering investors in assets are subject to noise trader risk in addition to fundamental risk, the average prices of assets would be below fundamental values. The main purpose of this thesis is to formulate a model to evaluate the impacts of investor sentiment on asset returns not only in terms of stock market indices but also on individual stock basis and economic sectors by measuring the effects of the demand shocks of noise traders on returns and volatility. Since EGARCH models are easy to interprete, have no non-negativity constraints on their coefficients, and convenient for modeling conditional volatility, an EGARCH model is proposed to determine whether investor sentiment increases the conditional variance whereas it lowers the returns undermining the risk-reward relationship. Several investor sentiment proxies are used such as Trading Volume, The American Association of Individual Investors (AAII), Put-Call Ratio, Baker & Wurgler Sentiment Index, and Chicago Board Options Exchange Market Volatility Index (VIX). Instead of using these investor sentiment proxies directly in the model, a regression analysis is carried out in order to control for macroeconomic shocks and distinguish noise trader behavior. A series of macro economic and monetary variables (Gross Domestic Product, Industrial Production, Producer Price Index, Consumer Price Index, Capacity Utilisation Rate, Long-term Interest Yields, and Monetary Supply) are used as independent variables and investor sentiment proxies are used as dependent variables in the regression analyses. The residuals of these regression analyses are used as indicators of investor sentiment in the EGARCH model.

The thesis is divided into three main parts that aim to provide substantial evidence for three different but interconnected hypotheses. In the first part, the study takes an international approach and uses the weekly returns of nine different stock market indices from U.S. (S&P500, NASDAQ, DJIA), U.K. (FTSE), Germany (DAX), France (CAC), Japan (NIKKEI), Hong Kong (HSI), and Turkey (ISE) as dependent variable. Weekly trading volumes of these indices are regressed against a group of macroeconomic variables and the residuals have been used as investor sentiment

proxies. There is significant evidence that there is asymmetric volatility in these market indices and earning shocks have more influence on conditional volatility when the sentiment is high.

The second part of the thesis explores the investor sentiment-conditional volatility relationship on an individual stock level. This part of the study also provides a better understanding of the impact of investor sentiment by using more than one investor sentiment proxy which has proven useful both in terms of comparison and verification purposes. All the stocks that are listed in S&P500 index through the years are divided into quintile portfolios according to their market capitalization and book-to-market ratio. The Market Capitalization ranked portfolios are equally weighted and the Book-to-market ranked portfolios are market capitalization weighted. The returns of these portfolios are used as dependent variable in the EGARCH model which has been previously used in the first hypothesis. In addition to trading volume, several other investor sentiment proxies are used such as, The American Association of Individual Investors (AAII), Put-Call Ratio, Baker & Wurgler Sentiment Index, and Chicago Board of Options Exchange Market Volatility Index (VIX). The EGARCH model is used to determine whether investor sentiment increases the conditional variance of small stocks (size effect) and growth stocks (book-to-market effect) more than it does for big stocks and value stocks. It has been found that market capitalization and book-to-market ratio have a considerable effect on the investor sentiment – conditional variance relationship where a rise in the investor sentiment especially increases the conditional variance of small stocks and growth stocks.

The last part of the thesis and the last hypothesis proposes that the effects of the investor sentiment vary for stocks from different economic sectors. A similar EGARCH model is used where the weekly returns of several sector indices of Istanbul Stock Exchange 100 (BIST100) is used as dependent variables and weekly trading volume of ISE 100 is used as investor sentiment proxy after controlling for macroeconomic shocks. There is significant evidence that a change in investor sentiment has more influence on conditional volatility of industry, banking, and food and beverages sector indexes when compared with other sectors such as retail or telecommunication.

YATIRIMCI DUYARLILIĞININ VARLIK GETİRİLERİNİN KOŞULLU DEĞİŞKENLİĞİNE ETKİSİ: ULUSLARASI BORSALARDAN ÖRNEKLER

ÖZET

Literatürde 80'lerin ortasından itibaren kendine yer bulan "Gürültü yatırımcı" kavramı, ilk elden, güvenilir bilgiye sahip olmayan ve irrasyonel yatırım kararları alan borsa yatırımcıları için kullanılmıştır. Diğer yatırımcılar rasyonel olmasına rağmen, gürültü yatırımcıların yüksek katılımı ile fiyatlardaki risk seviyelerini beklenen seviyelerden çok daha yüksek seviyelere taşıyabilir. Gürültü yatırımcı teorisindeki ilk varsayım, pazardaki tüm yatırımcıların tam anlamıyla rasyonel olmadığı ve bu yatırımcıların riskli varlıklar için taleplerinin, temel analiz bilgilerine dayandırılamayan bir çeşit yatırımcı kanaat veya duyarlılığından etkileneceğidir. İkinci varsayım ise, birinci varsayıma bağlı olarak, arbitrajın yatırımcı duyarlılığına tabi olduğu bu nedenle de riskli ve sınırlı olduğudur.

Gürültü yatırımcı teorisine göre hisse senedi fiyatlarının belirlenmesinde, standart risk faktörleri ve makroekonomik şokların yanısıra, rasyonel arbitrajcılar ile gürültü yatırımcıların birbirleriyle etkileşimi de önemli rol oynar. Bunun anlamı yatırımcı duyarlılığının da hisse senedi fiyatlarının belirlenmesinde önemli bir etken olduğudur. Naif ve deneyimsiz gürültü yatırımcılar riski ölçme ve bu konuda akıl yürütme konusunda zayıf olduklarından getirilerin varyansını, riskini hesaplarken ya da kestirirken iyi hesaplayamadıklarından, pazardaki risk-getiri ilişkisini zayıflatırlar. Literatürde sunulan bulgular da gürültü yatırımcıların, yatırımcı duyarlılığının daha yüksek olduğu dönemlerde borsada katılımının daha fazla olduğu ve daha agresif bir şekilde işlem yaptıkları yönündedir.

Hisse senedi pazarında gürültü yatırımcıların artan katılımı likidite sağladığı gibi, beraberinde gürültü yatırımcı riski, dolayısıyla fazladan volatilite de getirir. Ayrıca, hisse senedi pazarındaki yatırımcıların temel risklere ek olarak gürültü yatırımcı riskine de maruz kalmaları sonucunda, ortalama hisse senedi fiyatlarının olması gereken seviyelerin altına gerilediği gözlemlenir. Literatürdeki daha önce yapılan çalışmalara ek olarak bu tezin asıl amacı, yatırımcı duyarlılığının varlık getirileri üzerine etkilerini yalnızca borsa endeksleri bazında değil, tekil hisse bazında ve sektörler bazında da incelemektir. Bunu da gürültü yatırımcıların taleplerinin, varlık getirileri ve getirilerin volatiliteleri üzerinde yarattığı şokları ölçerek yapmak tezin birinci önceliğidir. Yatırımcı duyarlılığındaki artışların koşullu volatililteyi artırırken, getirileri düşürdüğünü ve bunun sonucunda pazardaki risk-getiri ilişkisini zayıflattığını kanıtlayabilmek ve açıklayabilmek için çalışmada EGARCH modeli kullanılmıştır. Bu modelin seçilmesindeki en önemli neden, eksponansiyel modeller olmaları sebebiyle EGARCH modellerin katsayıları üzerinde pozitif olma kısıtlamasının olmamasıdır. Bu da modelin hesaplamalarında ve yorumlamalarında esneklik ve kolaylık sağlar araştırmacıya. Tezde öne sürülen üç hipotezin ispatında da kullanılan EGARCH modellerde, incelenilen hipoteze dair hisse senedi ya da hisse senedi endeksinin haftalık getirisi bağımlı değişken olarak alınmıştır. Modelde

dışarıdan alınan değişken olarak, yatırımcı duyarlılığını temsil etmek amacı ile halihazırda literatürde kullanılan bir çok yatırımcı duyarlılığı ölçütü kullanılmıştır. Bunlar arasında işlem hacmi, American Bireysel Yatırımcı Derneği Endeksi, Put-Call rasyosu, Baker ve Wurgler Duyarlılık Endeksi, ve Şikago Opsiyon Borsası Pazarı Volatilite Endeksi bulunmaktadır. Bu yatırımcı duyarlılığı göstergeleri modelde doğrudan kullanılmak yerine önce makroekonomik şokları kontrol edebilmek ve 'gürültü yatırımcı' davranışını bu göstergelerin içinden daha iyi ayıklayabilmek için bir dizi makroekonomik değişken (Gayri Safi Milli Hasıla, Sanayi Üretim Endeksi, Üretici Fiyat Endeksi, Tüketici Fiyat Endeksi, Kapasite Kullanım Oranı, Uzun Vadeli Faiz Oranı, Kısa Vadeli Faiz Oranı, Parasal Kaynak (M1,M2)) ile regresyon analizi yapılmış, ve bu regresyon analizlerinin artiklari yatırımcı duyarlılığı göstergesi olarak modelde yer almıştır.

Tez üç ana bölüme ayrılmış olup, her bölüm farklı ama birbiriyle bağlantılı 3 ana hipoteze dair bulguları ve açıklamaları sunmaktadır. Tezin ilk bölümünde uluslararası bir bakış açısı ile hareket edilerek, dokuz farklı hisse senedi endeksinin haftalık getirileri bağımlı değişken olarak kullanılmıştır. Bu endeksler A.B.D.'den S&P 500, NASDAQ, DJIA; İngiltere'den FTSE 100; Almanya'dan DAX; Fransa'dan CAC; Japonya'dan NIKKEI; Hong Kong'dan HSI; Turkiye'den ise BIST 100 endeksleridir. Tezin bu ilk bölümünde, yatırımcı duyarlılığını temsil edebilmek için bu dokuz hisse senedi endeksinin haftalık işlem hacmi verileri kullanılmıştır. Fakat bu haftalık işlem hacimlerini etkileyen faktörler arasında, yatırımcıların bireysel düşünceleri ve kararları dışında makroekonomik gelişme ve şoklar da bulunmaktadır. Bu sebeple, dokuz hisse senedi endeksinin haftalık işlem hacmi verileri bağımlı değişken olarak alınarak, bir dizi makroekonomik değişken ile regresyon analizi yapılmış, ve bu regresyon analizlerinin artiklari yatırımcı duyarlılığı göstergesi olarak modelde yer almıştır. Yapılan analizlerde dokuz hisse senedi endeksinde de volatilitenin asimetrik olduğu gözlemlenmiştir. Yatırımcı duyarlılığının etkisine bakıldığında ise, yatırımcı duyarlılığındaki artışın getirileri düşürürken, koşullu volatiliteyi ise artırdığı görülmüştür. Bu durum normal şartlar altında kabul görmüş olan risk-getiri ilişkisine ters düşmektedir. Normal şartlar altında yatırımcı daha fazla risk aldığında, bunun karşılığını daha fazla getiri olarak alması gerekirken, yatırımcı duyarlılığının yüksek olduğu zamanlarda, başka bir deyişle 'gürültü yatırımcı''ların piyasada daha yoğun katılımda bulunduğu durumlarda, bu ilişki bozulmaktadır. Tezin ortaya koyduğu ilk hipotez bu dokuz hisse senedi endeksi ile kanıtlanmıştır: 'Piyasada yatırımcı duyarlılığının artışı, fiyatları baskılayarak, getirileri düşürür, koşullu volatiliteyi de artırır. Bunun sonucunda piyasadaki risk-getiri ilişkisinde bozulma yaşanır.'

Tezin ikinci bölümünde, yatırımcı duyarlılığı-koşullu volatilite ilişkisi hisse senedi endeksi yerine doğrudan hisse senedi bazında incelenmiştir. Yatırımcı duyarlılığının hisse senetleri üzerindeki etkilerini daha açık ve daha anlaşılır hale getirmek için tezin bu bölümünde yalnızca işlem hacmi değil, birden fazla yatırımcı duyarlılığı göstergesi kullanılarak hem karşılaştırma hem de hipotezleri doğrulama açısından model daha kullanışlı hale getirilmiştir. Hisse senedi bazında incelemeye geçmeden önce S&P 500 endeksinin haftalık getirileri bağımlı değişken olarak; haftalık işlem hacmi, American Bireysel Yatırımcı Derneği Endeksi, Put-Call rasyosu, Baker ve Wurgler Duyarlılık Endeksi, ve Şikago Opsiyon Borsası Pazarı Volatilite Endeksi de yatırımcı duyarlılığı göstergesi olarak kullanılmış, ilk bölümdeki hipotez bir defa daha farklı yatırımcı duyarlılığı göstergeleri kullanılarak da doğrulanmıştır. Bu doğrulama işlemi sonucunda, aynı zamanda hangi yatırımcı duyarlılığı göstergesinin modelin açıklama gücünü daha çok artırdığı da ortaya çıkmış, Put-Call rasyosunun diğer göstergelere göre daha iyi performans gösterdiği tespit edilmiştir.

Bu ikincil doğrulama işleminin ardından S&P 500 endeksinde 1994-2012 arasında listelenmiş tüm hisseler, piyasa değeri büyüklükleri ve piyasa değeri/defter değeri oranlarına göre gruplanarak, haftalık olarak %20'lik portföylere ayrılmıştır. Piyasa değerlerine göre sıralanmış %20'lik portföyler eşit olarak ağırlıklandırılmış olup, piyasa değeri/defter değeri oranlarına göre gruplanmış portföyler ise piyasa değerlerine göre ağırlıklandırılarak oluşturulmuştur. Bu oluşturulan portföylerin getirileri ise birinci hipotezde de kullanılan ana EGARCH modelinde bağımlı değişken olarak kullanılmıştır. Haftalık işlem hacmi verisine ek olarak, American Bireysel Yatırımcı Derneği Endeksi, Put-Call rasyosu, Baker ve Wurgler Duyarlılık Endeksi, ve Şikago Opsiyon Borsası Pazarı Volatilite Endeksi de yatırımcı duyarlılığı göstergesi olarak çalışmanın bu kısmında modelde yer almıştır. Gürültü yatırımcı teorisine de dayanarak, gürültü yatırımcıların piyasadaki artan varlığının yatırımcı duyarlılığını ve buna bağlı olarak da koşullu volatiliteyi artırdığı tezin ilk bölümünde açıkça belirtilmiştir. Bu gürültü yatırımcıların naif ve deneyimsiz olmaları, riski ölçme ve bu konuda akıl yürütme konusunda zayıf olmaları sonucunda, daha çok kazanç getireceğini umarak piyasa değeri küçük hisse senetlerine, ve piyasa değeri/defter değeri yüksek olan hisse senetlerine yönelmeleri beklenir. Buna bağlı olarak da bu tezdeki EGARCH modeli ile de test edilmek istenen, yatırımcı duyarlılığındaki artışların piyasa değeri küçük hisse senetlerinin ve piyasa değeri/defter değeri yüksek olan hisse senetlerinin koşullu volatilitesini büyük piyasa değeri ve piyasa değeri/defter değeri düşük olan hisse senetlerine göre daha fazla artırıp artırmadığıdır. Yapılan analizler sonucunda hisse senetlerinin piyasa değerleri ve piyasa değeri/defter değeri rasyolarının yatırımcı duyarlılığı-koşullu volatilite ilişkisi üzerinde önemli etkisi olduğu gözlemlenmiştir. Beklenen duruma paralel olarak, yatırımcı duyarlılığındaki bir artışın özellikle piyasa değeri küçük olan ve piyasa değeri/defter değeri yüksek olan hisse senetlerinin koşullu volatilitesini piyasa değeri büyük olan ve piyasa değeri/defter değeri düşük olan hisse senetlerine göre daha çok artırdığı gözlemlenmiştir. Yatırımcı duyarlılığının etkisinin büyüklüğü ayrı ayrı karşılaştırıldığında, gruplar arasındaki bu farkın istatistiksel olarak anlamlı olmamasının arkasında çalışmanın zaman aralığının çok uzun olması gösterilebilir. Bu tip anomaliler uzun vadede piyasada arbitrajcıların varlığı sebebiyle yalnızca kısa vadelerde anlamlı olabilir. İstatistiksel olarak anlamlı olmasa da aritmetik olarak belli bir farktan ve ilişkiden söz edilebilir.

Tezin son bölümünde, yatırımcı duyarlılığındaki değişimlerden belli sektörlerdeki hisse senetlerinin daha çok etkilenip etkilenmediği araştırılmıltır. Bu analizler için Borsa Istanbul'daki bazı sektör endekslerinin haftalık getirileri bağımlı değişken olarak kullanılmıştır. Birinci ve ikinci bölümlerde kullanılan EGARCH model, bu son bölümde biraz daha basitlestirilerek analize uygun hale getirilmiştir. Bu değişimdeki neden, sektörler için yapılan bu değerlendirmelerde yatırımcı duyarlılığının yalnızca koşullu volatilite ile ilişkisini incelemektir. Karşılaştırma ve serinin geçmişini sağlamadaki kolaylık göz önüne alındığında, ilk bölümdekine benzer olarak haftalık işlem hacminin yatırımcı duyarlılığı göstergesi olarak modelde yer alması uygun görülmüştür. Haftalık işlem hacmi verisi, makroekonomik şokları kontrol edebilmek ve yatırımcı davranışını daha iyi ayırt edebilmek için daha önce kullanılan makroekonomik verilerle regresyona alınmış, ve bu regresyon analizinin artiklari yatırımcı duyarlılığı göstergesi olarak modelde yer almıştır. Yapılan analizler sonucunda yatırımcı duyarlılığında yaşanan bir artışta, endüstri, banka ve gıda sektörlerine ait hisselerin koşullu volatilitesinin diğer sektörlere ait hisselere göre daha çok arttığı gözlemlenmiştir.

BIST 30 endeksinde listelenmiş olan hisseler, İstanbul Borsası'nda en yakından takip edilen ve hem kurumsal hem de bireysel yatırımcı bazında en çok işlem gören hisselerdir. Bu hisselerin çoğunluğunu bankacılık ve endüstri hisseleri oluşturur, ve bu sektör hisselerinin ağırlığı bu endekste diğer sektörlere göre daha fazladır. Yabancı takas verileri incelendiğinde de bu sektörlere ait hisselerin yabancılar tarafından daha çok ilgi gördüğü anlaşılmaktadır. İstanbul Borsası'nda işlem yapan hem kurumsal hem de bireysel yatırımcıların hemen hemen tümü yabancıların yatırım hareketlerini yakından izlemektedir. Gürültü yatırımcılar naif yatırımcılardır ve aldıkları yatırım kararları temel analize dayanmaz. Zamanlamaları kötüdür, trendleri takip ederler, ve iyi ya da kötü haberlere aşırı tepkiler verebilirler. Bütün bu bulgular, bankacılık ve endüstri sektörlerine ait hisselerin İstanbul Borsası'nda yönü belirleyici hisseler olduğunu, ve bu hisselerin gürültü yatırımcılar için diğer hisselere göre yatırım açısından daha cazip olduğunu göstermektedir. Tezin bu aşamasındaki bulgular gürültü yatırımcı teorisi ile de örtüşmektedir. Çünkü sürekli trendleri izleyen, sürü psikolojisine kapılan gürültü yatırımcıların, bankacılık ve endüstri sektörlerine ait hisselere talep göstermesi sonucu bu hisse senetlerinin fiyatları üzerinde baskı oluşu, koşullu volatiliteyi de artırır. Bu sebeple, İstanbul Borsası'nda bankacılık ve endüstri sektörlerine ait hisselerin koşullu volatilitesi, yatırımcı duyarlılığındaki değişimlerden daha çok etkilenmektedir.

1. INTRODUCTION

A generation ago, academic financial economists have acknowledged the efficient market hypothesis in general. It was widely assumed that securities markets were extremely efficient in reflecting information about individual stocks and about the stock market as a whole. The accepted thought was that when new information is released, the news spreads very fast and is reflected into the prices of securities without delay (Fama, 1970). So, neither technical analysis, which is the study of past stock prices in an attempt to predict future prices, nor even fundamental analysis, which is the analysis of financial information such as company earnings and asset values to help investors select "undervalued" stocks, would enable an investor to achieve returns greater than those that could be obtained by holding a randomly selected portfolio of individual stocks, at least not with comparable risk.

The idea of a “random walk” is associated with the efficient market hypothesis. It is a term usually employed in the literature of finance to demonstrate a price series where all subsequent price changes represent random departures from previous prices. The logic behind the idea of random walk is that if the flow of information is unhampered and stock prices instantaneously reflect the information, then the price change of tomorrow will reflect only tomorrow's news and will be independent of the price changes of today. Since news is by definition unpredictable, it is concluded that price changes must be unpredictable and random. As a result, prices fully reflect all known information, and even uninformed investors buying a diversified portfolio at the tableau of prices given by the market will obtain a rate of return as generous as that achieved by the experts (Malkiel, 2003).

The aforementioned efficient market hypothesis states that any mispricing in the market would be arbitraged away and the market will return to equilibrium prices. However, the history of the stock market is full of incidents contradicting with the theory such as The Great Crash of 1929, the Tronics Boom of the early 1960s, the Go-Go Years of the late 1960s, the Nifty Fifty bubble of the early 1970s, and the Black Monday crash of October 1987. The conventional finance model, where unemotional investors always force the markets to equal to the rational present value of expected future cash flows, has a considerable difficulty fitting these patterns (Baker & Wurgler, 2007).

Behavioral finance is a new approach in financial markets that has emerged as a response to the complications faced by the traditional finance theory. In general, behavioral finance argues that some financial phenomena can be better-apprehended using models in which some players are not fully rational. More definitely, it investigates what happens when one or both of the tenets that underlie individual rationality are relaxed (Barberis & Thaler, 2003). These financial phenomena that can be better understood by other means than efficient market hypothesis include short-term momentum, long-run reversals in addition to prediction patterns based on valuation parameters and firm characteristics such as dividend yields, P/E multiples, size effect and value/growth stocks.

A stock's price equals to its fundamental value, which is the discounted sum of expected future cash flows, in the traditional framework that players are rational and there are no frictions. Efficient Market Hypothesis (EMH) states that actual prices reflect fundamental values. Behavioral finance argues that some properties of asset prices are most reasonably considered as deviations from fundamental value, and that these deviations are caused by the presence of traders who are not fully rational. An attractive investment opportunity appears when there is a deviation from the fundamental value, which is a mispricing. Behavioral finance argues that when these investment opportunities are created, they are hard to be exploited immediately stating that the mispricing can be both risky and costly thus the mispricing can remain unexploited.

The most evident risk that an arbitrageur faces is the fundamental risk, which can be hedged to a limit by shorting a substitute security, but substitute securities are not always perfect making it impossible to remove all the fundamental risk. The arbitrageur will still be subject to risk that is specific to the portfolio he is holding. In addition to fundamental risk, there is also the noise trader risk which is an idea first introduced by De Long et al. (1990) studied further by Shleifer and Vishny (1997). Noise trader risk means that if the arbitrageur continues to exploit the mispricing, the situation becomes worse in the short-run. Even if the arbitrageur finds a perfect substitute for shorting, he is still subject to the risk that pessimistic investors who cause the stock to be undervalued in the first place become even more pessimistic and lower the price of the stock even more.

This thesis depends on noise trader approach that is an alternative to the efficient market theory. This approach is based on two main assumptions. First, not all the investors are fully rational and their demand for risky assets is influenced by their beliefs or sentiments that are not absolutely justified by fundamental news. Plainly speaking, the investors are subject to sentiment. Second, arbitrage which is stated as trading fully by rational investors not subject to any sentiment- is risky, thus limited (Shleifer & Summers, 1990). Therefore, betting against sentimental investors are costly and risky which can be stated limits to arbitrage in the language of modern behavioral finance.

The noise trader model states that there are limits to arbitrage and investors' beliefs are correlated, then noise which is unrelated to fundamentals, such as sentiment, may lead security prices to deviate from what is expected from the benchmark of market efficiency. This means that in addition to standard risk factors and macroeconomic variables, stock prices are determined by the interaction of rational arbitrageurs and noise traders. This phenomenon provides room for the presence of investor sentiment which can be defined as a representation of market players' beliefs about future cash flows relative to some objective standard, namely the true fundamental value of the underlying security.

Even though, there is some debate considering the significance of sentiment traders, one can logically make two cases. Firstly, sentiment traders exert greater influence during high-sentiment periods than during low-sentiment periods, since they are reluctant to take short positions in low-sentiment periods. It is also stated by empirical evidence that sentiment traders participate and trade more aggressively in high-sentiment periods (e.g. Karlsson, Loewenstein, and Seppi, 2005, and Yuan, 2008). The second case is that sentiment traders, who are naive and inexperienced, are likely to have a poor judgment of how to measure risk and as a result likely to misestimate the variance of returns which weakens the mean-variance relation.

Regarding the above indications, it must be noted that there is a critical role for investor sentiment in the mean-variance relation. When sentiment is low, there is a strong tradeoff between mean and variance as stated by the rational asset pricing theory which implies a positive relation over time between the markets' expected return and variance. But there is little tradeoff when sentiment is high because there is greater participation of traders that are driven by sentiment in the market when the investor sentiment is high which causes the prices to deviate from levels that would otherwise reflect a positive mean-variance tradeoff. Barber and Odean (2008) proved that since sentiment traders are more reluctant to take short positions in low-sentiment periods, they have much more effect on prices during high sentiment periods. The study of Yu and Yuan (2010) also showed that sentiment traders are likely to misestimate the variance of returns impairing the mean-variance relation since they tend to have a poor understanding of how to measure risk (Yu & Yuan, 2010).

Overall, the mean-variance relationship, which is the main tradeoff in finance, sets forth a strong tow-regime pattern and that investor sentiment can distinguish these two regimes uniquely. When investors that are driven by sentiment have a greater market participation which makes the sentiment high, this distorts prices away from levels that would otherwise reflect a positive mean-variance tradeoff.

The main objective of this thesis is to provide an international framework to model conditional volatility regarding the changes in the investor sentiment. In order to achieve this, this study is interested in measuring the effect of noise traders' demand shocks on the volatility of various stock markets both on the stock market index level and on individual portfolio level. Performing this process in a coherent way is compounded by the fact that there is no consensus on what kind of proxy to use when measuring individual sentiment for a given single stock market. This problem incidentally deteriorates when an attempt is made to procure a proxy that is available for different countries' stock markets.

Since there is the given recent detailed analysis of trading volume as a proxy for investor sentiment by Baker and Stein (2004), it seems reasonable and practical to employ this metric for the development of an investor sentiment proxy. First, it is easy to find available data of trading volume for many countries' stock markets and their listed securities. Second, it is available for long and reasonable periods for a wide range of stock market indices. In addition to these advantages, using trading volume as a proxy for investor sentiment seems to be the only coherent method to acquire a sentiment proxy that is largely comparable across countries.

Therefore, the main objective of this study is to test that whether the changes in an investor sentiment proxy that is constructed using trading volume have a significant effect on volatility and can be used to predict conditional volatility for both stock market indices and individual stock portfolios in different international stock markets.

In words, volatility refers to the degree to which financial prices fluctuate. Large volatility means that returns (that is: the relative price changes) fluctuate over a wide range of outcomes. The graph below illustrates what is often referred to as *time varying* volatility.

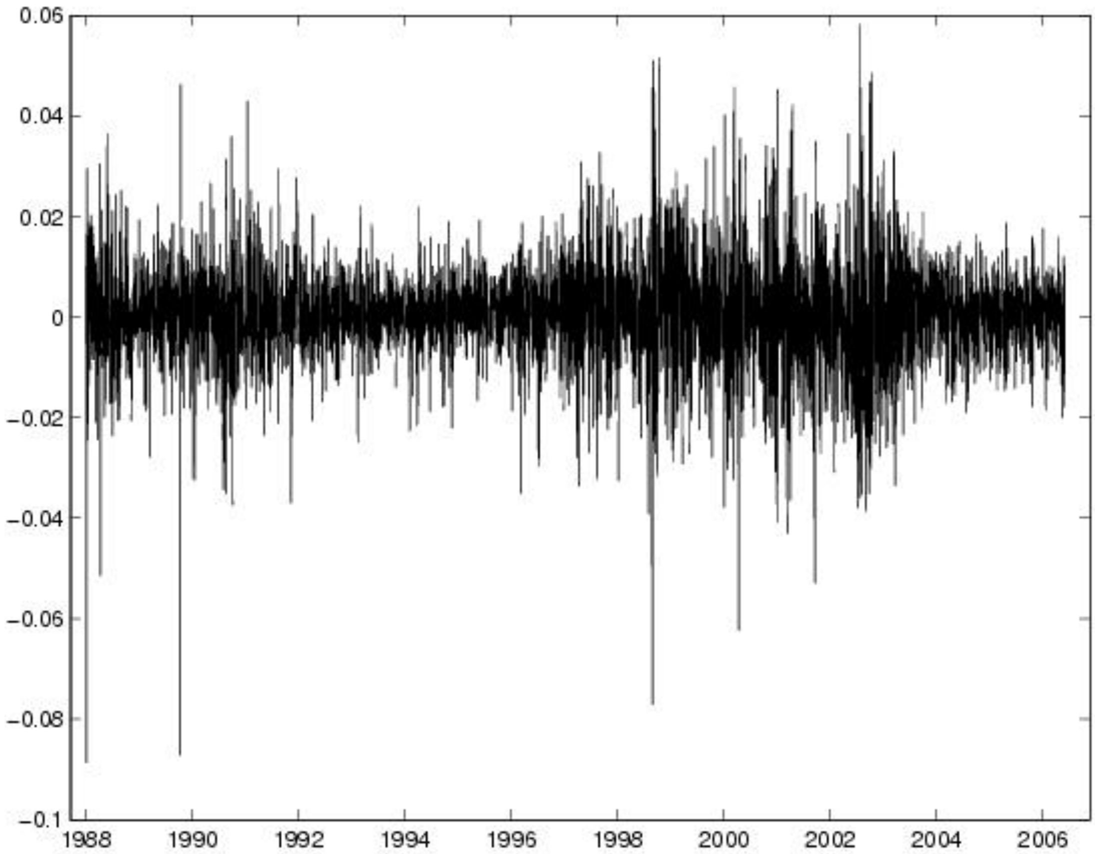

Figure 1.1 : Daily percentage changes in the value of the S&P 500 index over the period 1988-2006.

The figure demonstrates the daily percentage alterations in the S&P 500 index value over the period 1988-2006. It is obvious that there are intervals of small fluctuations (for example 1992-1996 and 2003-2006) and periods of large fluctuations (for example 1997-2003). This phenomenon is referred to as *volatility clustering,* and is the subject of a great amount of research in financial economics, as well as econometrics and mathematics. Volatile periods are hectic periods with large price fluctuations. Intuitively, such periods reflect investor uncertainty and one may suspect that such uncertainty is caused by uncertainty about the fundamentals in the economy. This has proven true to a certain extent. Uncertainty about fundamentals, however, is known to explain only a moderate portion of the observed financial market volatility. If one is interested in measuring and forecasting volatility, then simple time series models, or implied volatilities, still do a better job than looking at the fundamentals.

Many volatility models are employed in the finance literature for risk assessment. The Value-at-Risk (VaR) is probably the most widely used metrics to measure the market risk. The VaR could be viewed as a maximum loss of the given portfolio which is not exceeded with a given high probability (McNeil et al., 2005). Conditional risk management plays a key role for the purposes of financial clearing. By conditional risk management, we will understand the re-computing of key risk measures on a daily basis, given the changes in the market situation. Forecasting the conditional volatility is an essential element of dynamic risk management. This problem can be referred as volatility forecast, since the volatility at time $t + 1$ given data up to time t has be estimated. A disadvantage of linear stationary models is their failure to accommodate to changing volatility: The width of the estimation intervals remains constant even as new data become available, unless the parameters of the model are changed. In ARCH models, the estimation intervals are able to widen instantaneously to account for sudden changes in volatility, without changing the parameters of the model. Because of this property, using ARCH models have become a very considerable method in the analysis of economic time series.

A variety of ARCH models is employed in this thesis and a complete research is carried out to obtain the promised efficiency and accuracy in ARCH model estimation. Throughout this thesis, it is aimed to provide a framework based on ARCH models for the evaluation of noise trading shock demands by using an investor sentiment proxy which is derived from a series of computations with trading volume.

The thesis is organized as follows: First, the literature is reviewed (Section 2) thoroughly where noise trader theory, approach and its history are evaluated, different definitions and measurements of investor sentiment are discussed and different kind of effects and implementations of these investor sentiment measures are examined both on the stock market level and individual portfolio level. After the detailed literature review, the hypotheses of the thesis are summarized and a brief outline of the research questions are presented in Section 3. In Section 4, the methodology of thesis is discussed in comparison with the models used in previous studies regarding the effects of investor sentiment on stock markets. The main model is constructed among with the second and third models which are set to be used in evaluating the sector effects and individual portfolio effects respectively. In addition, the definition and the construction of the investor sentiment proxy that is used throughout this study is explained along with the construction method and the determination process of the dependent and independent variables used in the method to derive the new investor sentiment proxy in Section 4. The data concerning the stock markets indices, sector stock market indices and individual stocks are also explained in this section regarding how they are retrieved and chosen. It is also mentioned in how the portfolios are formed for the evaluation of the effects of sentiment on individual portfolios, which is one of the novelties along with the effects of sentiment on different economic sectors, provided in this thesis. Then the findings and the results of the thesis are demonstrated stating their contribution to the collective investor sentiment research area (Section 5). The last section (Section 6) is reserved for the discussions of the importance of the findings of the thesis and the further study to be carried out in order to have a better understanding of the ramifications of the investor sentiment concerning the stock markets.

2. LITERATURE REVIEW

2.1 Noise trader approach and the role of investor sentiment in asset valuation

If one assumes that the efficient markets hypothesis was a publicly traded security, its price would be extremely volatile. After Samuelson (1965) has proved that stock prices should follow a random walk if rational competitive players in the market require a fixed rate of return and Fama (1965) has demonstrated that stock prices are, in fact, close to a random walk, stock in the efficient markets hypothesis rallied. After the publication of Shillers's (1981) and Leroy and Porter's (1981) volatility tests, the stock in the efficient market hypothesis had a bear period, since these studies have showed that stock market volatility was far greater than could be justified by changes in dividends. Just after the studies of Kleidon (1986), Marsh, and Merton (1986), the hypothesis has found strong ground again. However, the papers of Shleifer and Summers (1990) and DeLong, Shleifer, Summers and Waldmann (1990) has demonstrated another aspect as noise trader risk that must be considered in addition to market volatility besides the rational expectations.

First assumption in the noise trader approach is that not all the investors in the market are fully rational and their demands for risky assets might be affected by their beliefs or sentiments that do not fully result from fundamental news. Second assumption is that arbitrage is subject to such sentiment, thus risky and therefore limited. Recent empirical studies have shown that cognitive biases and misguided beliefs that lead to suboptimal trading decisions might not be arbitraged away immediately, since individual investors are not only prone to biases as the population at large but also they might show over-confidence, herding behavior, and speculation (Barberis & Thaler, 2003). This suggests that noise, such as sentiment, is unrelated to fundamentals and this noise may well lead security prices to deviate from the expected benchmark of market efficiency. Therefore, the presence of the investor sentiment can be defined as a statement of market players' beliefs about future cash flows relative to some objective standard, which is the true fundamental value of the underlying security. Stock prices are determined by not only standard risk factors and macroeconomic influences but also by the interaction between the rational market players and noise traders.

There are two important points to be noted, although there is a considerable debate regarding the significance of sentiment traders. The first point is sentiment traders have a greater influence on the prices during high-sentiment periods than during low-sentiment periods because of their reluctance to take short positions in low-sentiment periods. The empirical evidence of Karlsson, Loewenstein, and Seppi (2005) and Yuan (2008) also suggest that sentiment traders participate and trade more aggressively in high-sentiment periods. The second point is that naïve and inexperienced noise traders would have a tendency to misjudge the amount of risk involved deteriorating the mean-variance tradeoff. Considering these notions, it is clear that investor sentiment has an important role in the mean-variance relation. There is a strong tradeoff between mean and variance during low-sentiment periods as the traditional asset pricing theory implies a positive relation over time between the markets' expected return and variance. However, the greater participation of noise traders which are driven by sentiment in the market during high-sentiment periods causes deviation in the prices from levels that would otherwise reflect a positive mean-variance tradeoff meaning that there would be little tradeoff. It is proved in the study of Barber and Odean (2008) that there is reluctance of noise (sentiment) traders to take short positions in low-sentiment periods so, they have a more drastic effect on prices during high-sentiment periods. Yu and Yuan (2010) also indicated that sentiment traders are likely to misestimate the variance of returns impairing the mean-variance relation since they tend to have a poor understanding of how to measure risk (Yu & Yuan, 2010).

The common result of all these studies is that news alone does not move stock prices: uninformed changes in demand move them too. These irrational demand changes seem to be a response to changes in expectations or sentiment that is not fully justified by information. In light of all these insights, it is concluded that investor sentiment plays an important role in the price determination of the stocks and, as a result, volatility modeling of the markets. In consequence, proper formulation and operational definition of an investor sentiment proxy is essential to build a robust model in order to assess the adverse effects of investor sentiment on the stock markets.

2.2 Defining and measuring investor sentiment

There has been no single widely acknowledged definition of investor sentiment to date. The definitions that exist in the literature vary from vague statements about investors' failures to more explicit psychological biases that are model-specific (Shefrin, 2007). Additionally, the term itself is classified in a wide spectrum and used in variety of ways by academic researchers, financial analysts, and the media (Barberis, Shleifer, Vishny 1998; Daniel, Hirshleifer, and Subrahmanyam 1998; Welch and Qiu 2004; Brown and Cliff 2004; Shefrin 2007; Baker and Wurgler 2007). For instance, some researchers might accredit investor sentiment as an inclination to trade on noise instead of information, while the same term is employed particularly to refer to investor optimism or pessimism. The sentiment term is also associated with emotions, thus the media accredit it as investor fear or risk-aversion.

In this research, it is subscribed to the approach that investor sentiment should be regarded in terms of beliefs. The classical definition of a rational investor is the one who has well-defined choices and develops accurate beliefs through Bayesian logic. It can be assumed that the former is always correct but the latter must be focused which means that investors are prone to incorrect beliefs but are otherwise rational in the sense that their choices fulfill standard preference axioms. Accordingly, throughout this thesis investor sentiment is defined as the representation of market players' beliefs about future cash flows in connection with some objective standard that is the correct fundamental value of the stock. In plain English, investors that are subject to sentiment might develop their beliefs not only through news about fundamentals but also irrelevant noisy signals and they might do so in a statistically incorrect way (Zhang, 2008).

Quantifying the investor sentiment has been a great concern in the finance literature and plentiful studies have been made since throughout the history of the financial markets there have been numerous historical events and empirical puzzles that are inconsistent with the efficient market hypothesis and other standard financial theories. Currently there are many sentiment measures, which range from measures that are developed for academic intentions to daily indices employed by traders for adverse objectives like closed-end fund discount, consumer confidence indices, investor intelligence surveys, market liquidity, implied volatility of index options, ratio of odd-lot sales to purchases, net mutual fund redemptions. Since there are numerous measures, it may be concluded that there is no consensus about which sentiment measure is more accurate and efficient. The disagreement is especially between the academic community and professionals because the latter one is employing these sentiment indices as an investment tool, while the former's sole purpose is to form arguments for or against market efficiency or to explain some irrationalities in the market.

The measurements of sentiment are examined in two subdivisions in this part of the thesis: Market based proxies for sentiment and direct surveys. The first one is the market-based approach that looks for extracting sentiment indirectly from financial proxies such as closed-end fund discount or put-call ratio. The second approach is measuring sentiment directly from investors using surveys and questionnaires. University of Michigan's Consumer Confidence Index and the Yale School of Management's Stock Market Confidence Index are examples for this kind of investor sentiment measure.

2.2.1 Market proxies for sentiment

There are many supporters for using market proxies for sentiment and they claim that specific financial data procure a dependable basis for sentiment approximation, although it is one-step removed from quantifying actual investor beliefs. Most of the market-based proxies are derived from empirical puzzles like closed-end fund discount and IPO underpricing.

Closed-End Fund Discount (CEFD)

If it is accepted that markets are efficient and arbitrage opportunities are exploited immediately, the fact that closed-end funds are traded at a discount is one of the most puzzling remarks in financial markets. Lee, Shleifer and Thaler, in their 1991 study, claim to demonstrate this anomaly in relation to investor sentiment. Ross (2005), Berk and Stanton (2004), Spiegel (1997), Chan, Kan, and Miller (1993), Malkiel (1977), and Zweig (1973) have provided rational explanations for this puzzle such as agency costs, illiquidity of assets, and tax liabilities. The study of Neal and Wheatley

(1998) examined the predictive ability of three widely used sentiment proxy: discounts on closed-end funds, the ratio of odd-lot sales to purchases, and net mutual fund redemptions. The findings suggested that discounts and net redemptions forecast the size premium but the odd-lot ratio is weak in predicting returns. Although CEFD is used as a consistent proxy for investor sentiment in many studies, Welch and Qiu (2004), Ross (2005), Chan, Kan and Miller (1993) have provided significant evidence that CEFD alone may not be sufficient to account for all investor sentiment because of omitted variable problem or confounding variables. Zang (2010) has used CEFD as a proxy for investor sentiment and provided evidence that excess volatility of closed-end fund prices and the synchronization of different funds' discount over time support the use of CEFD to indicate investor irrationality. Since small investors disproportionally hold closed-end funds, the supporters of the idea claim that CEFD is a suitable proxy for investor sentiment. Lei, Shleifer and Thaler (1991) have demonstrated that if decreases in the CEFD are positively correlated with asset returns held disproportionally by noise traders, then changes in the CEFD should be correlated negatively with retail sentiment. The authors showed confirming evidence that small firms outperform large firms when the CEFD decreases.

Option Implied Volatility (VIX)

When the value of the underlying asset has greater expected volatility, option prices rise and option pricing models such as the Black-Scholes formula can be employed to compute implied volatility as a function of option prices. Practitioners often call the Market Volatility Index (VIX) as the "investor fear gauge" and it measures the implied volatility of options on the Standard and Poor's 100 stock indices. Whaley (2000) reported that declines such as the crash of October 1987 or the 1998 Long Term Capital Management crisis happened right on times of big spikes in the VIX series.

Kurov (2010) used the VIX index constructed from the implied volatilities of S&P 500 index options to assess the effect of monetary policy decisions on the sentiment of stock market investors and found that monetary policy shocks have a strong impact on investor sentiment in bear market periods. It is also shown that sentiment sensitive stocks react more rapidly to monetary news.

Initial Public Offering (IPO) Data

It has been widely argued that initial public offerings (IPOs) can be explained by investor enthusiasm. Rational firms ought to exploit the dominating market sentiment to raise new equity so, IPOs might come in waves that relates to periods of over- or under-valuation. In addition to this, IPOs are subject ample underpricing. The equity that the companies sell tends to be underpriced resulting in a considerable price increase on the first day of trading, when these companies first go public.

Based on the above explanations and facts, it is assumed by some researchers that data on IPOs can be used as a proxy for investor sentiment. Welch and Qiu (2004) have constructed an index in their study based on violations of the law of one price in new equity issues. Baker and Wurgler (2007) have used high first-day returns on IPOs or IPO volume as a measure of investor eagerness. Even though IPOs and investor sentiment seems correlated, basing a sentiment measure solely on this data might not explain the situation properly and there might be confounding factors.

Dividend Premium

Stocks that pay dividend have common properties with bonds since they have a predictable income stream that demonstrates a noteworthy characteristic of safety. The relative premium for dividend-paying stocks is a price-based proxy and thought to be inversely related to sentiment. Baker and Wurgler (2004) have defined the dividend premium as the difference between the average market-to-book-value ratios of dividend payers and nonpayers. The dividend premium accounts for the major historical trends in firms' tendency to pay dividends, such as the post- 1977 decline indicated by Fama and French (2001). They documented that when dividends are at a premium, it is more likely that companies would pay them, and less likely so when they are at a discount. This suggests that firms seem to cater to prevailing sentiment for or against safety when they decide to pay dividend or not.

Mutual Fund Flows

It has been proposed by Brown, Goetzmann, Hirkai, Shiraishi, and Watanebe (2003) a general market sentiment measure based on how fund investors are moving into and out of safe government bond funds to risky growth stock funds. Acknowledging evidence has been suggested by Frazzini and Lamont (2008) using fund flows as a proxy for sentiment for individual stocks that when there is a considerable inflow to funds that hold a specific stock, the consecutive performance of that stock is relatively weak. Randall, Suk and Tully (2003) have used net cash flow into mutual funds as a measure for investor appetite and indicated that mutual fund flows have a predictive power in determining monthly stock market returns.

Trading Volume

Trading volume, or more commonly liquidity, can be used as a proxy for investor sentiment. It was noted in previous studies of Baker and Stein (2004) that if short selling is costlier than opening and closing positions, when irrational investors are optimistic and buying climbing stocks rather than when they are pessimistic and buying falling stocks, it is likely that they might want to trade and so, add liquidity. Kaniel, Saar and Titman (2004) have also formed an investor sentiment index called Net Investor Sentiment (NIS) by using individual buy and sell dollar volumes in NYSE. They have provided evidence that individual investors who trade on the NYSE are likely to react to the liquidity needs of institutions, and at least in the short run, gain abnormal returns by exploiting their counterparties demand for immediacy.

Other market proxies

Instead of using a single sentiment measure, Baker and Wurgler (2007) developed a sentiment index that averages six commonly used proxies for investor sentiment: trading volume based on NYSE turnover, the dividend premium, the closed-end fund discount, the number and first-day returns on IPOs, and the equity share in new issues. Each proxy is regressed on macroeconomic variables (industrial production, real growth in durable, non-durable, and services consumption, growth in employment, and NBER recession indicator) to get rid of the economic fundamental effects. Then principal component analysis is used to extract the common features into an averaged index. Baker & Wurgler (2007) have stated that when the sentiment is low(high), speculative stocks have greater(lower) future returns on average than bond-like stocks which shows that riskier stocks sometimes have lower expected returns inconsistent with classical asset pricing theories.

Wang (2003) used actual trader positions to forecast S&P 500 index futures returns and found that large speculator sentiment is a price continuation indicator while large hedger sentiment is a weak contrary indicator. Wang also used this investor sentiment proxy (2001) for forecasting purposes in agricultural futures markets and found similar results. It is also found that small trader sentiment hardly predicts future movements in the market. Dennis and Mayhew (2002) have used the Put-Call Ratio as a proxy for trading pressure and found that company-specific factors play a more important role than systematic factors in explaining the variation in the skew of individual companies. Lashgari (2000) utilized TED Spread, which is defined as the difference between the Treasury bill futures and the Eurodollar futures contracts, to explain the behavior of stock prices. The study showed that a contraction in spread means higher confidence in the stock markets whereas an increase in the spread means fear and escape to quality.

Retail investor trading activity is also exploited as a proxy for measuring the sentiment of the stock markets. It is argued that the inexperienced retail or individual investors are more prone to investor sentiment than the professionals are. It has been found that younger investors were more likely than older investors to buy stocks at the peak of the Internet Bubble (Greenwood and Nagel, 2009). Kumar and Lee (2006) have suggested in their paper to construct a sentiment index for retail investors based on whether such investors are buying or selling.

2.2.2 Survey measures of sentiment

Since survey measure of sentiment is a direct approach rather than using in direct market proxies for sentiment, using survey data for sentiment is a better way to capture the changes in the investors' mood, even though these survey measures of sentiment are subject to methodological issues and response biases.

University of Michigan Consumer Confidence Index

Since 1978, The Michigan Consumer Research Center supplies a consumer confidence index derived from monthly surveys of consumers. The survey is based on 500 telephone interviews with adult men and women from United States and five questions are asked to respondents to capture their mood swings and current confidence in the economy.

Lemmon and Portniaguina (2006) have used Michigan Consumer Confidence Index as a proxy for investor sentiment in their recent work, a time series framework is adopted in their study and it is shown that consumer confidence helps to reveal the time variation in equity portfolio returns, specifically size premium. The authors have employed a similar method as Baker and Wurgler (2006) has used in which the proxy for sentiment is regressed on a group of macroeconomic variables. In addition to CEFD, Qiu and Welch (2004) have also used Michigan Consumer Confidence to show that sentiment changes affect the excess return of stocks especially with small market capitalization. Fisher and Statman (2003) have exploited the Conference Board Consumer Confidence Index and Michigan Consumer Confidence Index for purposes of stock price prediction and found that there is a negative relationship between the level of consumer confidence in 1 month and stock returns in the next month and next 6 and 12 months.

American Association of Individual Investors Sentiment Survey

Brown (1999) has used the direct measure of investor sentiment data collected for the American Association of Individual Investors (AAII) Sentiment Survey. Since 1987, AAII has selected randomly a group of its members and surveyed them on a weekly basis. They ask their respondents where they think the stock market will be in six months: bullish, bearish or neutral. Brown (1999) has provided strong evidence that individual investor sentiment is related to increased volatility in closed end funds (CEF) which is also a supporting evidence both for the reason that why CEFD is employed as an investor sentiment proxy. These findings are also consistent with the DSSW theory that irrational investors act together on a noisy signal as sentiment can effect asset prices and create added risk.

Not all the studies are focused only on returns since there are recent works that also inquire the effect of investor sentiment on conditional volatility using the above stated sentiment proxies. W. Y. Lee et al. (2002) utilized Investors' Intelligence of New Rochelle, which is recognized as a reliable forecaster of market movements. 135 independent advisory services are read and rated by the editor of Investors' Intelligence's editor each week. Letters are rated as bullish, bearish or correction depending on the prediction of the market. The sentiment index is calculated as the ratio of the number of bullish investment advisory services relative to the total number of all bullish and bearish investment advisory services. W. Y. Lee et al employed a GARCH-in-mean model to test for the effects of sentiment on returns and volatility, which is displayed by equations (2.1) and (2.2):

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 h_{it} + \alpha_2 Jan_t + \alpha_3 Oct_t + \Delta S_t + \varepsilon_{it} \tag{2.1}$$

$$h_{it} = \beta_0 + \beta_1(\varepsilon_{it-1})^2 + \beta_2(\varepsilon_{it-1})^2 I_{t-1} + \beta_3 h_{it-1} + \beta_4 R_{ft} + \beta_5(\Delta S_{t-1})^2 D_{t-1} + \beta_6(\Delta S_{t-1})^2(1 - D_{t-1}) \tag{2.2}$$

Where R_{it} is the weekly return on a market index, R_{ft} is the risk-free rate, ΔS_t is the measure of nose trader risk regarding the weekly changes in the Investors' Intelligence Sentiment, h_{it} is the conditional volatility of the market index, and I_t and D_t are dummy variables to test the asymmetric effects of the sentiment and earning shocks. The study showed that changes in the sentiment are negatively correlated with the market conditional volatility which means volatility goes up (goes down) if investors become more bearish (bullish).

It is also investigated by Verma & Verma (2007) that fundamental and noise trading has relative effects on conditional volatility and unlike previous studies they focus on both the rational and noise components of investor sentiment and their relative effects on volatility making a separation between rational and irrational investor sentiment. Unlike the study of W. Y. Lee et al. (2002), AAII investor sentiment index is employed in this research and instead of a GARCH model they have used EGARCH model to test for the asymmetric effects of sentiment. They have found that there is greater effect of bullish than bearish investor sentiments on the volatility of stocks. They have also stated that stock returns' effect on individual investor sentiment (institutional investor sentiment) is significant (insignificant) which suggests that individuals are mostly positive feedback traders.

Wang et al. (2009) have used GJR-GARCH, EGB_2, and SWARCH models to investigate for the sentiment effect on the Taiwan Futures Exchange. Wang (2001) has developed an investor sentiment index for each type of trader based on their current total positions and historical extreme values as follows:

$$SI_t = (Open_t - \min[Open_t]) / (\max[Open_t] - \min[Open_t]) \tag{2.3}$$

Where SI_t is the sentiment index, $Open_t$ is the open interest position at day t, and *max [$Open_t$]* and *min [$Open_t$]* are maximum and minimum positions over the sample period. A more recent work has been Yu and Yuan's (2010) research, which also uses GARCH models and Baker and Wurgler's (2006) composite sentiment index that is mentioned before. They separated the sampling period into two as high sentiment regime and low sentiment regime. The mean-variance relation is tested with the following model:

$$R_{t+1} = a + bhVar_t(R_{t+1}) + \varepsilon_{t+1} \qquad \textbf{(2.4)}$$

$$R_{t+1} = a_1 + b_1 hVar_t(R_{t+1}) + a_2 D_t + b_2 D_t Var_t(R_{t+1}) + \varepsilon_{t+1} \qquad \textbf{(2.5)}$$

Where R_{t+1} is the monthly excess return, $Var_t(R_{t+1})$ is the conditional variance, and D_t is the dummy variable for the high sentiment period, which is, D_t equals one if month t is in a high sentiment period. The empirical results found in the study support the aspect that mean-variance tradeoff changes with the sentiment. It is found that there is a significantly positive tradeoff in the low sentiment period (b_1 is 13.075 with a t-statistic of 2.45) but this is dramatically weakened (b_2 is -13.714 with a t-statistic of -2.64) in the high sentiment period. There are also studies that focus on the effects of returns on investor sentiment rather than exploring the effects of investor sentiment on returns. The study of Lutz (2012) focused on the effects of returns on investor sentiment instead. A common factor from the returns of hard-to-value and difficult-to-arbitrage stocks is used and it is found that high returns forecast high sentiment and low fear. This suggests noise trader driving the investor sentiment follow positive feedback strategies. Lutz also used the returns on-lottery like stocks and a dynamic factor model to construct a new index for investor sentiment (2013) which is highly correlated with other sentiment indicators. Lutz found that the sentiment-future returns relationship is positive but considerably weak during sentiment expansions in contrast to sentiment contraction periods where high sentiment forecasts low returns for the cross-section of speculative stocks and for the overall market. Fisher and Statman (2000) also suggested that stock returns are unmistakably the most important factors that affect sentiment. They found significant relationship between S&P 500 returns and future changes in the individual investor sentiment. Clarke and Statman (1998) provided evidence that past returns and the volatility of those returns affect the investor sentiment. Their research showed that high returns over 4-week periods leads the newsletters migrate from being bearish to bullish and high returns over periods of 26 and 52 weeks leads them from being bearish to bullish and correction. A more detailed list of studies that utilize the aforementioned proxies and other investor sentiment measures is given in Table 2.1.

Table 2.1 : Detailed list of the utilized proxies, their measurements and related studies.

PROXY	MEASUREMENT	STUDIES
Optimism / Pessimism about the economy		
Index of Consumer Confidence	Survey by Conference Board www.conferenceboard.org	Fisher & Statman (2003)
Mischigan Consumer Confidence Index	Survey by University of Mischigan	Fisher & Statman (2003) Lemmon & Portniaguina (2006) Qiu & Welch (2004)
Optimism / Pessimism about the stock market		
Put / Call Ratio	Puts outstanding Calls outstanding	Dennis and Mayhew (2002)
Retail investor trades	Portfolio's BSI over a particular time period	Kumar & Lee (2006)
Mutual Fund Cash Positions	Net cash flow into MF's	Randall, Suk, and Tully (2003) Frazzini and Lamont (2005)
Mutual Fund redemptions	Net redemptions/total assets	Neal and Wheatley (1998)
AAII Survey	Survey of individual investors	Brown (1999) Fisher & Statman (2000) Fisher & Statman (2003)
Investors' Intelligence of New Rochelle	Survey of newsletter writers	W. Y. Lee et al. (2002)
TED Spread	Tbill futures yield – Eurodollar futures yield	Lashgari (2000)
Riskiness of the Stock Market		
Issuance %	Gross annual equities issued Gross ann. debt & equ. Issued	Baker & Wurgler (2006) Welch and Qiu (2004)
RIPO	Avg. ann. first-day returns on IPO's	Baker & Wurgler (2006)
Dividend premium	Difference between the average market-to-book-value ratios of dividend payers and nonpayers	Baker and Wurgler (2004)
Turnover	Reported sh.vol./avg shs listed NYSE (logged & detrended)	Baker & Wurgler (2006)
Closed-end fund discount	Y/E, value wtd. avg. disc. on closed-end mutual funds	Baker & Wurgler (2006) Neal and Wheatley (1998) Lee, Schleifer, & Thaler (1991) Chopra, Lee, Schleifer, & Thaler (1993)
Market liquidity	Reported share volume Avg # of shares	Baker & Stein (2004)
Risk Aversion		
VIX – Investor Fear Gauge	Implied option volatility	Whaley (2000) Kurov (2010)

2.3 Effects of sentiment on concerning different stock attributes

Investigating stock market anomalies that are defined as empirical findings that contradict with the Efficient Market Hypothesis have been one of the most intriguing subjects of the behavioral finance literature. These anomalies are also used to test the efficiency of the markets that they exist within. Some of these stock market anomalies are periodical such as day of the week effects, seasonality effects related to the months, or holiday effects. Some of the anomalies are inherent in the stock itself such as P/E effect, book-to-market effect (value vs. growth), firm size effect, trading volume effect etc. It is logical that one might expect that all these anomalies, which the investors try to exploit to make greater returns, are sentiment driven since noise trader hypothesis suggests that not all the investors are fully rational and their demand for risky assets is influenced by their beliefs or sentiments that are not absolutely justified by fundamental news.

It has been widely argued that investor sentiment has an adverse effect on returns and volatility of stock markets and all the studies mentioned before provide sustainable evidence for the importance of investor sentiment regarding stock valuations in the financial the markets. Nevertheless, the investor sentiment might have adverse effects on different kind of stock. For example, small or illiquid stocks may be more prone to the changes in the investor sentiment that changes in the investor sentiment might have more severe effects on returns and volatility of these stocks. These adverse effects might also be high book-to-market ratio or nature of the stock such as being an industrial, technological, service etc. Thus, the effect of the investor sentiment on these market anomalies and the effect of the investor sentiment on the stock market volatility regarding these stock-inherent anomalies should be investigated.

Chan & Fong (2004) have employed a parsimonious method to test the forecasting capability of the announcement of the individual investors’ sentiment for the coming week’s return by regressing weekly return on the percentage of optimistic stock investors in the proceeding Friday evening Survey. A similar methodology that has been used by Fisher and Statman (2000) is employed:

$$R_w = \alpha + \beta P_{w-1} + \varepsilon_w \tag{2.6}$$

Where R_w is the return from the market close on Friday of week *w-1* to the market close on Friday of week *w*, and P_{w-1} is the percentage of stock investors in the survey of Friday evening of week *w-1* being optimistic about R_w minus the sample mean of the percentage of optimistic stock investors. They have investigated that whether the release of individual investor sentiment data temporarily affects the prices hence the returns of the stocks in a market where investor sentiment is likely to be influential.

In fact, they have found that publication does not predict the coming week's return on large, medium, or small stocks but it was observed that the publication affects the daily closing prices of medium and small stocks, but not large stocks where the effect was stronger for small stocks than for medium stocks.

Baker and Wurgler (2007) have defined some stocks as speculative regarding their risky appeal that they are harder to arbitrage. The stocks are divided in several ways such as firm age, market capitalization, dividend payment, profitability, and growth and distress indicators like market-to-book ratio, asset growth or sales growth. They have stated that older, larger, dividend paying; profitable stocks are easier to arbitrage. The effect of investor sentiment on the returns of different kind of stocks according to these indicators is investigated and it has been found that sentiment betas increase as stocks become more speculative and harder to arbitrage meaning that the changes in the sentiment has more effect on speculative stocks' returns.

The effect of investor sentiment on small stocks is investigated by other researchers too. Qui & Welch (2004) have stated their hypothesis that sentiment changes disproportionally influence small stocks and found that Michigan Consumer Confidence Index exerts an influence on the small firm spread more than it does for stocks with large market capitalization.

Kaniel et al. (2004) have implemented a different analysis of investor sentiment(by constructing NIS mentioned before) in addition to how investor sentiment effects stock returns stating that there is an interaction between trading volume, investor sentiment and stock returns. Kumar and Lee (2006) have developed an investor sentiment index similar to the study of Kaniel et al. (2004) with dollar-denominated buy and sell volumes called BSI, which is a directional net retail sentiment indicator. BSI is calculated. The model employed to investigate the effect of sentiment on returns is as follows:

$$\begin{aligned} R_{pt} - R_{ft} &= \alpha_p + \beta_{1p} RMRF_t + \beta_{2p} SMB_t + \beta_{3p} HML_t \\ &+ \beta_{4p} UMD_t + \beta_{5p} BSI_t + \varepsilon_{pt} \end{aligned} \tag{2.7}$$

Where, R_{pt} is the portfolio rate of return, R_{ft} is the risk-free rate of return; $RMRF_t$ is the market return in excess of the risk-free rate. The beta of SMB and HML terms are to test the effect of sentiment on market capitalization and book-to-market ratio. In addition to small firm factor, Kumar & Lee (2006) found that the changes in the retail investor sentiment have additional explanatory power also for value stocks, stocks with low institutional ownership, and stocks with lower prices. The stated association showed that the stocks in these portfolios experience higher excess returns when retail investors become relatively bullish. Moreover, Schmeling (2009) used a long-horizon return regression of the form:

$$\frac{1}{K}\sum_{K=1}^{k} r_{t+K} = \delta_0 + \delta_1\, sent_t^i + \Psi_t\, \gamma + \xi_t \qquad \textbf{(2.8)}$$

With the average k-period return where Ψ_t is the set of macro variables such as annual CPI inflation, annual change in industrial production, term spread, the dividend yield, and the 6 months interest rate. The study provided significant evidence that value stocks are more dramatically affected by the sentiment changes.

Besides the researches that investigate the relation between investor sentiment and stock returns, there has also been some evidence regarding the effects of investor sentiment on volatility of returns concerning stocks with different attributes. As mentioned before, W. Y. Lee et al. (2002) have focused on the relation between the changes in the sentiment index and the market volatility with the model previously displayed as Equations 2.1 and 2.2. They have demonstrated that the most important effect was on NASDAQ’s volatility, which is consistent with the study of Lee et al. (1991) since, individual investors are not only dominant readers of independent investment advisory newsletters but also the prevailing shareholders of small capitalization stocks. But this research did not focus on the effect of sentiment on stock inherent market anomalies and their relation regarding the mean-variance tradeoff since the study only observed the main indices NASDAQ, S&P500, and DJIA and not evaluate the effects on stock basis employing these effects as a variable in the main model without elaborating on them specifically.

Hu and Wang (2012) found that stocks that have low book-to-market ratio and high Price/Earnings are more prone to investor sentiment since they are regarded as harder to arbitrage. They used a similar sentiment proxy like Baker and Wurgler’s (2007) and stated that these stocks experience higher (lower) excess returns when investors are bullish (bearish). Bathia and Bredin (2012) used a group of sentiment proxies and examined the effect of sentiment on the returns of value stocks, growth stocks and overall G7 market. The study provided evidence that when investor sentiment increases, the returns decreases affecting the value stocks especially.

2.4 Effects of sentiment on stock markets in different economic time spans: Recessions, expansions, crises

The literature of psychology strongly suggests that decision making process and particularly information processing are affected by emotions. For instance, Tiedens and Linton (2001) indicated that emotions determine the reliance on heuristic versus systematic processing. Smith and Ellsworth (1985), Ortony, Clore, and Collins (1988) have also expressed that sense of uncertainty is considerably associated with anxiety, hope and sadness. Gino, Wood, and Schweitzer (2009) exhibited that anxiety makes subjects more willing to take advice, even if the advice is bad. This means that if the agents are primed into negative mood states, their decision-making capabilities also change. It is reasonable to argue that investors are happy and optimistic in expansion periods, whereas they are mostly fearful and anxious during recessions. Investors experience job losses and uncertainty over future during recessions and this put the population at large in negative mood states. It is evident that investors are especially sensitive to news in economic downturns and they tend to follow different decision-making processes in recession periods opposed to expansion periods.

Shiller (2000) has constructed a speculative bubble index, a negative bubble index and an index for investor confidence to explain the behavior of individual and institutional investors throughout recession, expansion and crisis periods. It has been found that these indicators have an apparent relation with the lagged change in stock prices. Moreover, the bubble expectation index and the consumer confidence index have been observed to be very low during the recessions. Chung et al. (2012) have developed a Markov-switching model and employed Baker and Wurgler's (2007) sentiment proxy to investigate the effect of sentiment on returns considering different economic regimes. The study demonstrated that the forecasting capacity of sentiment for returns increases in expansion regimes whereas it decreases in recession regimes. Garcia (2013), on the other hand, constructed a measure of sentiment based on financial news from New York Times during 1905 to 2005 and found that news content helps forecasting stock returns at daily frequency especially during recession periods indicating that investor sentiment has a significant effect particularly in bad times.

Siegel (1992) investigated whether there would be another factor that explained the stock market crash of October 1987 beside the fundamental variables and suggested that changes in the investor sentiment induced by noise traders was another factor that caused the stocks to decline. Investor Intelligence is utilized in the study as a proxy and it has been found that a significant component of stock returns during the stock market crash were driven by unexpected shifts in the investor sentiment. Zouaoui et al. (2010) have used consumer confidence index whether the investor sentiment has an influence on the probability of stock market crisis. It is found that investor sentiment increases the likeliness of a stock market crisis happening within a one-year horizon. It is also stated in the study that the influence of the investor sentiment on the stock markets is more prominent in countries that are culturally more prone to herd-like behavior and overreaction or in countries with low institutional involvement.

3. HYPOTHESES

In the very first part of the thesis, this thesis employs weekly trading volume of the stock market indices of several countries as a proxy for individual investor sentiment similar to previous researches. Instead of using survey data or other sentiment indices, a new sentiment proxy is formed in order to capture the effects of investor sentiment on the returns and conditional volatility of stock markets. Weekly trading volume data of these market indices are used as a proxy for investor sentiment. Baker and Stein (2004) have provided an analysis in detail of employing trading volume as a proxy for investor sentiment. Trading volume is available for many countries' stock market indices and their listed securities and it is usually available for long periods. Therefore, the changes in the trading volume of stock market indices of the regarding countries are used as individual investor sentiment indices. Since the changes in the trading volume are not only indicators of noise trader behavior but also outcomes of many macroeconomic events, trading volume data is not directly used as a proxy for investor sentiment. Weekly trading volume data is regressed against a group of macroeconomic variables: Industrial Production, Producers Price Index, Consumers Price Index, Gross Domestic Product and Capacity Utilization Rate. In fact, there is no consensus for choosing a suitable proxy when evaluating the individual investor sentiment of a single country.

The DeLong, Shleifer, Summers and Waldmann's (1990) prediction is that stocks disproportionally held by sentiment (noise) traders are disproportionally subject to investor sentiment. Based on not only on empirical but also theoretical evidence, it is commonly understood that investor sentiment should be mean-reverting. Baker and Wurgler's (2007) sentiment index followed a mean-reverting walk. It has also been argued that overconfidence might lead to a mean-reverting difference of opinions among different investors (Scheinkman and Xiong, 2003). Since the sentiment follows a mean-reverting process, the distribution of sentiment conditional when the investor sentiment is high should have a longer right tail. Higher sentiment would push the prices up and lowers the expected returns so; the return distribution would be left skewed. Accordingly, noise (sentiment) traders have more effect on prices of the stocks in high sentiment periods. Therefore, one might expect to find that all the moments of realized variance in high sentiment periods are greatly higher than low sentiment periods which show that prices are more volatile when the investor sentiment is high. So the first hypothesis is formed as follows:

Hypothesis 1: During high investor sentiment periods, earning shocks have more influence on the conditional volatility meaning that high sentiment should weaken the mean-variance relation.

Many of the mentioned studies focus on the return side of the mean-variance relationship instead of the conditional volatility of stock markets and the researches that address the issues about the conditional volatility of stocks lack to check for adverse effects of sentiment for stocks with different attributes. Some stock market anomalies are inherent in the stocks themselves and since some stocks are difficult to arbitrage, it must be investigated whether the investor sentiment alters the mean-variance relationship much more dramatically for these kinds of stocks. It must also be noted that all these studies lack the understanding to address this problem on an international basis checking for different effects in different countries and making comparisons between markets. So, the second hypothesis is formulated as follows:

Hypothesis 2: During high investor sentiment periods, earnings shocks have more influence on the conditional volatility of stocks that are harder to value and/or arbitrage such as growth stocks (book-to-market effect) and small stocks (firm size effect).

In addition, not all these researches focused on the effects of sentiment on different economic sectors since the researches only investigated the main indices and not examined the effects on basis of sectors without elaborating on them specifically. This research, on the other hand, explores whether some sectors are more prone to the changes in the investor sentiment or not so that an increase in the participation of sentiment traders in the stock market undermines the mean-variance tradeoff more dramatically. Therefore, unlike previous researches, one of the main purposes of this study is to provide a better understanding regarding the impacts of investor sentiment on conditional volatility of stock markets belonging to different kind of economic sectors.

Noise (sentiment) traders who are naive and uninformed may not realize the market risk as informed traders do. These naive sentiment traders tend to follow the trends in the market in a herds behavior since most of the times they do not take their time to make valuations or assessments regarding the stocks in the market, and when they do, they usually end up misinterpreting the inherent risk-return relationship in the market, thus have a defected risk perception. So, it is natural to expect that these naive sentiment traders would focus on stocks which are most commonly (heavily) traded, or in other words, stocks which are key driving factors in the trend setting of that particular stock market index. Stocks belonging to sectors such as banking, financial services or industry are usually the trend setting stocks in their respective stock market indices and these are the key driving sectors in the economy. As the participation of the sentiment traders increases in the market, one expects that these stocks are affected more dramatically from the changes in the investor sentiment. Hence, it is logical to anticipate that stocks belonging to some particular economic sector would be more prone to the changes in the investor sentiment than others. In light of these reasoning, the third hypothesis is formed as follows:

Hypothesis 3: During high investor sentiment periods, earnings shocks have more influence on the conditional volatility of stocks belonging to sectors, which are the key driving factors in the economy such as banking, financial services, and industry.

4. DATA & METHODOLOGY

Volatility refers to the degree to which financial prices fluctuate. Large volatility means that returns- the relative price changes- fluctuate over a wide range of outcomes. Figure 1.1 previously mentioned in the introduction section illustrates a natural phenomenon that has often been referred to as time varying volatility.

The graph displays the daily percentage changes in the value of the S&P 500 index over the period 1988-2006. There are clearly periods of small fluctuations (for example 1992-1996 and 2003-2006) and periods of large fluctuations (for example 1997-2003). This phenomenon is known as *volatility clustering*, and is the object of a great deal of research in financial economics, as well as econometrics and mathematics. Volatile periods are hectic periods with large price fluctuations. Intuitively, such periods reflect investor uncertainty and one may suspect that such uncertainty is caused by uncertainty about the fundamentals in the economy. This has proven true to a certain extent. Uncertainty about fundamentals, however, is known to explain only a moderate portion of the observed financial market volatility. If one is interested in measuring and forecasting volatility, then simple time series models, or implied volatilities, still do a better job than looking at the fundamentals.

Many volatility models are employed in the finance literature for risk assessment. The Value-at-Risk (VAR) is probably the most widely used metrics to measure the market risk. The VAR could be viewed as a maximum loss of the given portfolio which is not exceeded with a given high probability (McNeil et al., 2005). Conditional risk management plays a key role for the purposes of financial clearing. By conditional risk management we will understand the re-computing of key risk measures on a daily basis, given the changes in the market situation. Forecasting the conditional volatility is an essential element of dynamic risk management. This problem can be referred as volatility forecast, since the volatility at time $t + 1$ given data up to time t has be estimated. A disadvantage of linear stationary models is their failure to accommodate to changing volatility: The width of the estimation intervals remains constant even as new data become available, unless the parameters of the model are changed. In ARCH models, the estimation intervals are able to widen instantaneously to account for sudden changes in volatility, without changing the parameters of the model. Because of this property, using ARCH models have become a very considerable method in the analysis of economic time series.

Engle (2001) proposed that data suffers from *heteroscedasticity* when the variance of the error terms is not equal and the error terms might fairly be expected to be larger for some points or ranges of the data than for others. A simple autoregressive method such as ARMA would be insufficient for modelling non-constant variances conditional on the past with heteroscedasticity present in the data because the standard errors and confidence intervals calculated by standard methods would be too narrow, even though the coefficients for an ordinary least squares regression are still unbiased. ARCH and GARCH models consider heteroscedasticity as a variance to be modeled instead of assuming it as a problem.

The equation of generalized GARCH model for variance is seen as below as the variance of the residuals of a regression $r_t = m_t + \sqrt{h}_t\varepsilon_t$ is denoted as h_t: employed:

$$h_{t+1} = \omega + \alpha(r_t - m_t)^2 + \beta h_t = \omega + \alpha h_t \varepsilon_t^{\ 2} + \beta h_t \tag{4.1}$$

where the constant ω, and the coefficients α, β *are to be forecasted*. The above GARCH model is typically called GARCH (1.1). The first number in the parentheses refers to how many autoregressive lags, or ARCH terms exist in the equation whereas the second term refers to how many moving average lags are specified which is called the number of GARCH terms. Engle (1982) modeled the ARCH mechanisms as serially uncorrelated processes with non-constant variances conditional on the past, but constant unconditional variances. The conditional variance, h_t, is a function of past squared returns in the first ARCH model suggested by Engle (1982), whereas further dependencies were used in the equation of conditional variance in GARCH models proposed by Bollerslev (1986). The EGARCH modeled by Nelson (1991) constructs conditional variance in logarithmic form. By employing logarithmic form imposing non-negativity constraints is not necessary. In EGARCH a negative shock leads to a higher conditional variance in the following period than a positive shock (Poon and Granger, 2003). Another model that allows for nonsymmetrical dependencies is GJR-GARCH, which is developed by Lawrence Glosten, Ravi Jagannathan, and David Runkle (1993). Glosten et al. (1993) showed that the standard GARCH-M model is inaccurately specified. They readdressed the problem and altered the model to allow positive and negative innovations to returns to have different impacts on the conditional variance. They also demonstrated that the results did not change when they used EGARCH-M specification. The paper suggested a negative relation between volatility and expected return and it is found that persistent of volatility is quite low in monthly data.

Lee et al. (2002) has used Investors' Intelligence Index as a proxy for investor sentiment and proposed a GARCH-M model that has simultaneous changes in investor sentiment in the mean equation and lagged changes in the magnitude of investor sentiment in the variance equation. They have found that the changes in the sentiment are negatively correlated with the market volatility and sentiment has the most drastic impact on NASDAQ consistent with CEFD's high correlation with the smallest stocks. Verma and Verma (2007), on the other hand, have used a two-step method. In the first step, they have examined the associated impact of individual and institutional investor sentiments on stock volatility as theorized by De Long et al. (1990). Second, they have explored whether rational risk factors or noise drives the impacts of sentiment on volatility. A multivariate E-GARCH model has been used and AAII investor sentiment has been chosen as a proxy and they have found that it is more likely for individuals to be positive feedback traders. The study of Wang et al. (2009) is one of the recent works that uses GARCH methodology where GJR-GARCH, EGB_2 and SWARCH methods are used in order to assess the effects of investor sentiment on the Taiwan Futures Exchange. The GJR-GARCH model to test the asymmetric effects of the sentiment is as follows:

$$\mu_t = \theta_o + \theta_1 h_t + \theta_2 \Delta SI_t + \varepsilon_t \tag{4.2}$$

$$\begin{aligned} h_t = {} & \gamma_0 + \gamma_1 {\varepsilon_{t-1}}^2 + \gamma_2 {\varepsilon_{t-1}}^2 I_{t-1} + \gamma_3 h_{t-1} + \gamma_4 R_f + \gamma_5 (\Delta SI_{t-1})^2 D_{t-1} \\ & + \gamma_5 (\Delta SI_{t-1})^2 (1 - D_{t-1}) \end{aligned} \tag{4.3}$$

Where D_{t-1} is a dummy variable that $D_{t-1} = 0$ if $\Delta\ SI_{t-1} < 0$; and $D_{t-1} = 1$ if $\Delta\ SI_{t-1} > 0$. Another recent study of Yu and Yuan (2010) has demonstrated the investor sentiment has a considerable effect on the mean-variance tradeoff using GARCH (1, 1).

This research tries to take a middle course and optimize a sound model among these previous ARCH models by building the main model with the better parts of each one. The late GARCH models that Yu and Yuan (2010) have employed are easy to use and interprete but they come with several limitations and disadvantages. On the other hand, EGARCH models are also easy to use and interprete and they have fewer limitations. The following sections explain the methodology and the data set that have been used for the support and verification of each hypothesis in detail.

4.1 Hypothesis I: Effects of investor sentiment on main stock market indices

The main purpose of this thesis is to formulate a model to evaluate the adverse effects of investor sentiment on both stock market index and individual stock level instead of the previous studies that have focused solely on main market indices. The study also investigates the effects of the investor sentiment on stocks operating in different kind of economic sectors in order to check whether the investor sentiment's effects alter for different economic sectors.

An EGARCH model is suggested in this thesis for overcoming the non-negativity constraints and understanding the asymmetric effects more clearly.

$$\mu_t = \theta_o + \theta_1 Sent_t + \varepsilon_t \tag{4.4}$$

$$\begin{aligned} \log(h_t) = \gamma_0 + \gamma_1[|\,\varepsilon_{t-1}/\sigma_{t-1} - \sqrt{2/\pi}\;\;] + \gamma_2(\varepsilon_{t-1}/\sigma_{t-1}) + \gamma_3 \log(h_{t-1}) \\ + \gamma_4 Sent_{t-1} \end{aligned} \tag{4.5}$$

In the mean equation, $Sent_t$ is the respective investor sentiment indicator controlled for macroeconomic shocks. Thus, θ_1 is the indicator for the sentiment's effect on the returns. In the variance equations, ε_{t-1} is the First-Order autoregressive lag term. γ_2 coefficient shows the impact of negative innovations to returns and is the indicator of leverage effect whereas γ_3 shows the persistence in the volatility. A high persistence might suggest a modelling for the long-term variance as well. The coefficient γ_4 in the variance equation is the indicator for the sentiment's effect on the conditional variance. This EGARCH model is used for the verification and support of all the hypotheses in the thesis where only the returns and the investor sentiment proxies employed in the respective hypothesis are changed.

For the first part of the study, weekly stock market index returns of U.S. (NASDAQ, DJIA, S&P 500), Japan (NIKKEI 225), Hong Kong (HANG SENG), U.K. (FTSE 100), France (CAC 40), Germany (DAX), and Turkey (BIST 100) from the year 2000 to 2012 have been used as dependent variables taking an international approach. Instead of using survey data or other sentiment indices, a new sentiment proxy has been constructed in order to capture the effects of investor sentiment on the returns and conditional volatility of stock markets. In the recent study of Uygur and Taş (2012) the changes in the weekly trading volume data of 9 market indices were used as a proxy for investor sentiment. Since the changes in the trading volume are not only indicators of noise trader behavior but also outcomes of many macroeconomic events, trading volume data is not directly used as a proxy for investor sentiment in this research. Weekly trading volume data is regressed against a group of macroeconomic variables to control the macroeconomic shocks: Industrial Production, Producers Price Index, Consumers Price Index, Gross Domestic Product and Capacity Utilization Rate, Long-term Bond Yields, and Money Supply. Since the macroeconomic variables are mostly on released on a monthly or quarterly basis, there has been a need to transform these control variables to a weekly frequency. Cubic spline interpolation method has been used to transform the monthly and quarterly frequency of control variables to weekly frequency. All the weekly closing prices and their weekly trading volume data of the nine market indices and all the macroeconomic variables of the countries whose market indices are used have been retrieved from Bloomberg.

4.2 Hypothesis II: Effects of investor sentiment on growth vs. value stocks

Before continuing with the second part of the thesis, a preliminary analysis has been carried to clarify some of the points previously mentioned in the verification of the first hypothesis. The EGARCH model has been applied to the weekly S&P 500 index's return itself for five different investor sentiment proxies (Trading Volume, AAII, Put/Call Ratio, VIX, and Baker & Wurgler sentiment index) for the verification of the main hypothesis that investor sentiment should pressure and lower the returns whereas the growing presence of noise traders should increase the volatility. The same method used previously for controlling for the macroeconomic shocks has also been utilized for the four other investor sentiment proxies. The same sets of macroeconomic and monetary variables for S&P 500 have been used, and their frequencies have been transformed by using cubic spline interpolation to weekly frequency. The determining cause for choosing the S&P 500 is the fact that a long historical data of S&P 500 is available and it is convenient and easy to find consistent and established investor sentiment proxies regarding the U.S. stock market.

For testing the second hypothesis, instead of using the stock market index returns as has been done in the first part of the thesis, weekly returns of the stocks that are listed in the S&P500 from the year 1994 to 2012 are used to understand the effects of investor sentiment on stocks with different attributes. All the stocks that are listed in S&P500 index through the years are divided into quintile portfolios according to their market capitalization and book-to-market ratio. The Market Capitalization ranked portfolios are equally weighted and the Book-to-market ranked portfolios are market capitalization weighted. The returns of these portfolios are used as dependent variable in the EGARCH model. θ_2 and γ_4 coefficients shows the impacts of investor sentiment on the respective portfolio's return and variance. It is expected θ_2 to be negative and γ_4 to be positive and statistically significant since the increase in the investor sentiment means higher participation of noise traders that lowers the returns and increases the variance distorting the mean-variance relationship. For proxying the investor sentiment, some of the main indicators widely used in the literature like Trading Volume, AAII (American Association of Individual Investors), Put/Call Ratio, VIX (Chicago Board Options Exchange Market Volatility Index), and Baker & Wurgler sentiment index (2007) have been employed in the study. The changes in these sentiment proxies are not the only indicators of noise trader behavior but also outcomes of many macroeconomic events. Thus, these proxies are regressed against a group of macroeconomic variables such as Industrial Production, Producers Price Index, Consumers Price Index, Gross Domestic Product and Capacity Utilization Rate, Long Term Interest Rate, Money Supply similar to the Baker and Wurgler (2007) study. The same sets of macroeconomic and monetary variables for S&P 500 have been used, and their frequencies have been transformed by using cubic spline interpolation to weekly frequency. The residuals of these regressions have been used as investor sentiment proxies like previously done in the first hypothesis testing. All relevant data has been retrieved from Bloomberg.

4.3 Hypothesis III: Effects of investor sentiment for different economic sectors

The main purpose of this paper is to formulate a model to evaluate the adverse effects of investor sentiment on different kind of sector indices in Istanbul Stock Exchange (ISE). Weekly returns of sector indices of ISE from the year 2002 to 2012 are used in the study. Instead of using survey data or other sentiment indices, a new sentiment proxy is formed in order to capture the effects of investor sentiment on the returns and conditional volatility of stock markets. Trading volume is the most suitable and practical investor sentiment proxy that could be employed with a study focusing on Istanbul Stock Exchange since other survey measures such as Turkish Statistical Institute Consumer Confidence Index or CNBCE Consumer Confidence Index fail to go back to early years or capture the riskiness of the stock market. Baker and Stein (2004), and Kaniel et al. (2004) have employed trading volume as an investor sentiment proxy and they have indicated that irrational investors are optimistic and buying climbing stocks rather than when they are pessimistic and buying falling stocks, it is likely that they might want to trade and so, add liquidity. These irrational investors increasing the liquidity by constant buying and selling cause an increase in price volatility and this suggestion is also consistent with noise trader theory.

Weekly trading volume data of Istanbul Stock Exchange 100 (ISE 100) has been used as a proxy for investor sentiment. Since the changes in the trading volume are not only indicators of noise trader behavior but also outcomes of many macroeconomic events, trading volume data is not directly used as a proxy for investor sentiment. Similar to the Baker and Wurgler (2007) study, weekly trading volume data is regressed against a group of macroeconomic variables: Industrial Production, Producers Price Index, Consumers Price Index, Gross Domestic Product, Capacity Utilization Rate, Long Term Interest Rate, and Money Supply. The residuals of this regression analysis is used an indicator of investor sentiment controlling the effects of the macro economical events on the noise trader behavior. The same frequency transformation method to enable the regression analysis has also been used in this section. All the weekly closing prices and weekly trading volume data of the market indices and all the macroeconomic variables of the countries have been retrieved from FINNET.

An EGARCH model has been suggested in this study for overcoming the non-negativity constraints and understanding the asymmetric effects more clearly.

$$\mu_t = \theta_o + \varepsilon_t \tag{4.6}$$

$$\log(h_t) = \gamma_0 + \gamma_1[|\varepsilon_{t-1}/\sigma_{t-1} - \sqrt{2/\pi}\ ] + \gamma_2(\varepsilon_{t-1}/\sigma_{t-1}) + \gamma_3 \log(h_{t-1}) + \gamma_4 \Delta Sent_{t-1} \tag{4.7}$$

Weekly returns of seven different sector indices of ISE from the year 2002 to 2012 have been used as dependent variables in the EGARCH model. In the mean equation, μ_t is the return of the respective sector index, and θ_0 is the constant term. In the variance equation, *ht* is the conditional volatility of the market index, ε_{t-1} is the First-Order autoregressive lag term, and $\Delta Sent_{t-1}$ is the change in the investor sentiment indicator controlled for macroeconomic factors. γ_2 coefficient shows the impact of negative innovations to returns whereas γ_3 shows the persistence of volatility. The coefficient γ_4 shows the impact of a change in investor sentiment on the respective ISE sector index's conditional variance. It is expected γ_4 to be positive and statistically significant since an increase in the investor sentiment means higher participation of noise traders whose constant buying and selling increases the price volatility, which is in line with noise trader theory stated by DeLong et al. (1991).

The main concern of this part of the research is to check whether a hike in investor sentiment causes a greater increase the conditional variance of the stocks in particular economic sectors. The main EGARCH model has been altered to better fit the data with minor modifications. $\Delta Sent_{t-1}$ has been used in the model instead of $Sent_{t-1}$ since it was observed that the coefficient for $Sent_{t-1}$ in the first study was statistically insignificant for BIST100 returns. The change in the sentiment indicator rather than the level of the indicator has been employed in the main EGARCH model where the momentum in the investor sentiment is significant.

The regarding coefficient (γ_4) is reported and compared among each ISE sector index in order to understand whether the effect of the investor sentiment on conditional volatility differs for various sector indices.

5. RESULTS

5.1 The effects of investor sentiment on international stock markets

The first part of the results section of the thesis is dedicated to the main hypothesis that an increase in the investor sentiment decreases the returns and increases the conditional volatility.

The descriptive statistics of the nine market indices are shown below in Table 5.1. Through the observed years, only CAC and NIKKEI indices had a negative mean return and all the other markets experienced a positive return. All the markets are negatively skewed which indicates a distribution with an asymmetric tail extending to negative values meaning frequent past small gains and a few past extreme losses. CAC, FTSE and NIKKEI markets are the ones with the highly skewed distributions. High kurtosis has been observed during the period in all the markets that points out a leptokurtic distribution indicating fatter tails and lesser risk or extreme losses or gains. Jarque–Bera statistics also indicate that the distributions of the residuals are not normal.

Table 5.1 : Descriptive statistics of the nine observed stock market indices.

	BIST	*SNP*	*DOW*	*NAQ*	*DAX*	*CAC*	*FTSE*	*HANG*	*NIK*
Mean	0.0036	0.0003	0.0005	0.0009	0.0005	−0.0005	0.0002	0.0010	−0.00046
Median	0.0064	0.0015	0.0029	0.0020	0.0040	0.0023	0.0019	0.0025	0.0025
Maximum	0.2578	0.1136	0.1070	0.1037	0.1494	0.1243	0.1258	0.1172	0.1145
Minimum	−0.1927	−0.2008	−0.2002	−0.1660	−0.243	−0.2505	−0.2363	−0.1781	−0.2788
SD	0.0451	0.0268	0.0255	0.0309	0.0353	0.0329	0.0269	0.0323	0.0317
Skewness	−0.0115	−0.8065	−0.8466	−0.3992	−0.7301	−1.0912	−1.3374	−0.2478	−1.4411
Kurtosis	6.0272	10.2751	11.0365	5.1609	8.4522	9.9572	16.1473	5.8046	14.3746
Jarque–Bera	203.53	1,233.22	1,498.01	117.86	707.53	1,180.72	3,997.67	180.14	3,057.83
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	1.9148	0.1561	0.2877	0.4617	0.2570	−0.2869	0.1134	0.5489	−0.2451
Sum sq. dev.	1.0829	0.3818	0.3450	0.5095	0.6637	0.5750	0.3851	0.5537	0.5332

Firstly, instead of using survey data or other sentiment indices, a new sentiment proxy has been constructed in order to capture the effects of investor sentiment on the returns and conditional volatility of stock markets. In the recent study of Uygur and Taş (2012) the changes in the weekly trading volume data of 9 market indices were used as a proxy for investor sentiment. Since the changes in the trading volume are not only indicators of noise trader behavior but also outcomes of many macroeconomic events, trading volume data is not directly used as a proxy for investor sentiment in this research. Weekly trading volume data is regressed against a group of macroeconomic variables to control the macroeconomic shocks: Industrial Production, Producers Price Index, Consumers Price Index, Gross Domestic Product and Capacity Utilization Rate, Long-term Bond Yields, and Money Supply. The residuals from these regressions have been used as investor sentiment proxy in the main EGARCH model as the "$Sent_t$" variable. Weekly stock market index returns of U.S. (NASDAQ, DJIA, S&P 500), Japan (NIKKEI 225), Hong Kong (HANG SENG), U.K. (FTSE 100), France (CAC 40), Germany (DAX), and Turkey (BIST 100) from the year 2000 to 2012 have used as dependent variables.

The results of the main EGARCH model for the first hypothesis are presented in Table 5.2. Coefficient θ_1 is checked to see the effect of higher sentiment on returns indicating whether higher investor sentiment has a negative effect on returns since it is expected that higher sentiment, which means more participation of noise traders, should put pressure on the prices and lower the returns. θ_1 is significant and negative for all the markets except BIST 100, NIKKEI and HSI market indices which indicates that as the investor sentiment and the participation of noise traders increase, the returns decrease.

Table 5.2 : EGARCH Results for the first hypothesis.

coeff.	*BIST*	*SNP*	*DOW*	*NAQ*	*DAX*	*CAC*	*FTSE*	*HANG*	*NIK*
θ_0	0.0052	0.0011	0.0003	0.0015	-0.0002	-0.0025	0.0001	0.0007	0.0004
	2.8977**	1.3918	0.2552	1.2619	-0.2002	-2.7151**	0.0926	0.6579	0.2942
θ_1	8.87E-07	-3.13E-12	-1.62E-11	-3.05E-12	-2.93E-02	-3.53E-11	-2.30E-12	-1.46E-04	-9.28E-13
	1.2783	-5.8044**	-5.2395**	-3.6307**	-6.2496**	-6.763**	-4.6153**	-0.5714	-1.4150
γ_0	-0.2502	-7.3943	-7.3237	-6.7119	-0.9436	-0.5325	-7.2924	-0.6490	-6.9627
	-2.1746*	-5.8721**	-7.0047**	-1.5489	-5.2848**	-4.6584**	-6.8026**	-4.2998**	-3.4225**
γ_1	0.1184	0.0100	0.0100	0.0100	0.1461	0.0787	0.0100	0.1383	0.0100
	3.1935**	0.2217	0.1347	0.3483	2.5018*	1.6590	0.2268	2.8234**	0.1672
γ_2	-0.0422	0.0100	0.0100	0.0100	-0.2562	-0.2335	0.0100	-0.1255	0.0100
	-2.3815*	0.3174	0.2289	0.4065	-8.8561**	-8.2913**	0.2644	-4.5663**	0.2146
γ_3	0.97571	0.01000	0.01000	0.01000	0.88436	0.93414	0.00998	0.92450	0.01000
	62.1503**	0.0582	0.0671	0.0156	38.7239**	65.3861**	0.0676	48.3967**	0.0343
γ_4	5.64E-06	1.12E-10	7.43E-10	3.52E-11	4.28E-01	2.82E-10	9.87E-11	9.76E-03	1.03E-10
	1.5107	7.3278**	7.385**	3.1924**	4.8782**	2.8088**	5.6411**	3.0417**	2.2915*
R-squared	0.0032	0.0166	0.0105	0.0106	0.0251	0.0281	0.0235	0.0006	0.0027
Adjusted R-squared	0.0014	0.0156	0.0090	0.0095	0.0236	0.0267	0.0221	-0.0009	0.0008
Akaike info criterion	-3.567017	-4.560462	-4.51768	-3.859461	-4.244162	-4.38138	-4.447401	-4.188179	-4.107923
Schwarz criterion	-3.5116	-4.5258	-4.4710	-3.8233	-4.1975	-4.3347	-4.4007	-4.1415	-4.0504
Hannan-Quinn criter.	-3.5454	-4.5473	-4.4996	-3.8457	-4.2261	-4.3633	-4.4293	-4.1701	-4.0854

The first figures are the coefficients themselves. The smaller figures are t-statistics of the coefficients. * & ** means %5 and %1 statistical significance respectively.

In order to check the asymmetric volatility in the model, the coefficient γ_2 should be checked. If γ_2 is significant and negative, negative shocks have a greater effect on h_t than positive shocks. γ_2 is significant and negative for ISE, DAX, CAC, HSI stock market indices pointing out that bad news generates more volatility in these respective markets. The γ_3 parameter measures the persistence in conditional volatility irrespective of anything occurring in the market. If γ_3 is relatively large, volatility takes a long time to die out following a crisis in the market. Similar to the asymmetric volatility case, ISE, DAX, CAC, HSI stock market indices seem to show high persistence since γ_3 is high, positive, and statistically significant demonstrating that long-term variance might to be modeled also to have a better insight.

The coefficients γ_4 is to be evaluated in order to check the effect of investor sentiment on the conditional volatility. Because of the substantial participation of sentiment (noise) traders during high-sentiment periods undermining an otherwise positive mean–variance tradeoff in the stock market, it is expected that γ_4 should be positive whereas θ_1 should be negative. It is observed that the coefficient γ_4 is positive and statistically significant for all the stock market indices except ISE (although it is also significant at 10% level for ISE). Noise traders are naïve players whose buying and selling decisions do not base on the use of fundamental data, their timing is poor and they follow trends, and over-react to good and bad news. These findings are logical and in line with the noise trader theory because noise traders' enduring activity of buys and sells puts pressures on the prices and increase the volatility. Noise trader theory proposes that earning shocks have greater impact on the conditional volatility in high sentiment periods that indicates that high sentiment should weaken the mean–variance relation. The results from these first findings regarding the main market indices of several countries support noise trader theory since the greater participation of sentiment traders undermines the positive mean–variance tradeoff causing by increasing the volatility and decreasing the returns contrary to the rational risk-reward relation.

5.2 The effects of investor sentiment on stock markets: Size effect and book-to-market effect

The main purpose of this part of the research is to formulate a model to evaluate the adverse effects of investor sentiment on a stock level instead of the previous studies that have focused solely on main market indices. Weekly returns of the stocks that are listed in the S&P500 from the year 1994 to 2012 have been used to understand the effects of investor sentiment on stocks with different attributes. The investor sentiment, some of the main indicators widely used in the literature like Trading Volume, AAII (American Association of Individual Investors), Put/Call Ratio, and Baker & Wurgler sentiment index (2007) have been employed in the study as an investor sentiment proxy. Due to the fact that the changes in these sentiment proxies are not the only indicators of noise trader behavior but also outcomes of many macroeconomic events, the five sentiment proxies are regressed against a group of macroeconomic variables such as Industrial Production, Producers Price Index, Consumers Price Index, Gross Domestic Product and Capacity Utilization Rate, Long Term Interest Rate. This method is similar to the Baker and Wurgler (2007) study in the sense of using macroeconomic and monetary control variables. The residuals of these regressions have been used as investor sentiment proxies. All data has been retrieved from Bloomberg.

The below main EGARCH model is used in this part of the study for overcoming the non-negativity constraints and understanding the asymmetric effects more clearly.

$$\mu_t = \theta_o + \theta_1 Sent_t + \varepsilon_t \tag{5.1}$$

$$\log(h_t) = \gamma_0 + \gamma_1 [| \varepsilon_{t-1} / \sigma_{t-1} - \sqrt{2/\pi} \;] + \gamma_2 (\varepsilon_{t-1} / \sigma_{t-1}) + \gamma_3 \log(h_{t-1}) + \gamma_4 Sent_{t-1} \tag{5.2}$$

h_t is the conditional volatility of the market index, $Sent_t$ is the respective investor sentiment indicator controlled for macroeconomic factors. In the variance equations, ε_{t-1} is the First-Order autoregressive lag term. γ_2 coefficient shows the impact of negative innovations to returns. All the stocks that are listed in S&P500 index through the years are divided into quintile portfolios according to their market capitalization and book-to-market ratio. The Market Capitalization ranked portfolios are equally weighted and the Book-to-market ranked portfolios are market capitalization weighted. The returns of these portfolios are used as dependent variable in the EGARCH model. θ_1 and γ_4 coefficients shows the impacts of investor sentiment on the respective portfolio's return and variance. It is expected θ_1 to be negative and γ_4 to be positive and statistically significant since the increase in the investor sentiment means higher participation of noise traders that lowers the returns and increases the variance distorting the mean-variance relationship.

The main concern of this particular section of the thesis is dedicated to check whether investor sentiment increases the conditional variance of small stocks and growth stocks more than it does for big stocks and value stocks. The regarding coefficient (γ_4) is reported and compared among each quintile portfolio in order to understand whether the effect of the investor sentiment is getting higher as the market capitalization and the book-to-market ratio gets smaller.

Table 5.3 below summarizes the descriptive statistics for the five investor sentiment proxies. In contrast to the returns, investor sentiment indicators have positive skewness that shows a distribution with an asymmetric tail extending to positive values. This polarity between the skewness statistics is also consistent with the theory since the DSSW theory and our EGARCH model suggest that an increase in the investor sentiment decreases the returns.

Table 5.3 : Descriptive statistics of the five investor sentiment proxies.

	VOLUME	*PUT/CALL*	*AAII*	*VIX*	*BWURGLER*
Mean	-21736046	0.000905	-0.003876	0.268566	0.179834
Median	-67476751	-0.014321	-0.015166	-0.888516	0.045284
Maximum	5890000000	0.464493	0.500126	53.08841	2.496648
Minimum	-5.5E+09	-0.254065	-0.454614	-10.99587	-0.90244
Std. Dev.	1350000000	0.11818	0.175841	6.892137	0.585029
Skewness	0.338332	0.572487	0.237187	2.902633	1.629015
Kurtosis	4.457986	3.379766	2.614385	17.37085	6.164017
Jarque-Bera	85.9046	48.38503	12.42651	7987.396	685.8067
Probability	0	0	0.002003	0	0
Sum	-1.73E+10	0.721969	-3.092676	214.3159	143.5074
Sum Sq. Dev.	1.45E+21	11.13133	24.64322	37858.74	272.7805

A correlation analysis has also been performed in order to assess whether there are comovements between the investor sentiment proxies. Table 5.4 presents the results of the correlation analysis. The first figures are the correlations and the second figures in italics are the statistics for significance. Although most of the correlations are statistically significant, the levels are not high enough to suggest duplicate use of investor sentiment proxies. It would be logical to infer that these five investor sentiment proxies all capture a different aspect of the noise trader behavior.

Table 5.4 : Descriptive statistics of the nine observed stock market indices.

	BWURGLER	***PUT/CALL***	***VOLUME***	***VIX***	***AAII***
BWURGLER	1 -----				
PUT/CALL	0.120626 *0.0006*	1 -----			
VOLUME	0.13644 *0.0001*	0.29322 *0*	1 -----		
VIX	-0.052182 *0.1408*	0.19152 *0*	0.23592 *0*	1 -----	
AAII	0.062186 *0.0792*	0.303376 *0*	0.260347 *0*	0.311806 *0*	1 -----

Firstly, the EGARCH model is applied to the S&P500 index's return itself for four different investor sentiment proxies (Trading Volume, AAII, Put/Call Ratio, and Baker & Wurgler sentiment index) for the verification of the main hypothesis that investor sentiment should pressure and lower the returns whereas the growing presence of noise traders should increase the volatility. Table 5.5 gives the summary of the EGARCH model applied to the S&P500 index's return. The first figures are the coefficients themselves. The figures in brackets are t-statistics of the coefficients. * & ** means 5% and %1 statistical significance respectively. These are valid for all the tables in this section.

It can be observed from the higher R-squared and Akaike information criterion that the performance of the Put/Call Ratio proxy is slightly better than the four other investor sentiment proxies. It has been observed that there is positive volatility feedback for Put/Call Ratio and AAII since θ_1 is positive and statistically significant. It is also found that γ_2 is negative and statistically significant except for Trading Volume indicating there is negative leverage effect for AAII, Put/Call Ratio and Baker & Wurgler Index. Higher and statistically significant γ_3 coefficients for these three proxies also demonstrate that there is high persistence in volatility for S&P500. As expected, the coefficient θ_1 is negative, and γ_4 is positive and they are statistically significant pointing that an increase in the investor sentiment, which means higher participation of noise traders, lowers the returns and increases the variance distorting the mean-variance relationship. Hence, all the investor sentiment indicators proved that the for the S&P500 index itself that as the investor sentiment increases the return decreases and the conditional variance increases undermining the mean-variance relation. These findings provided additional evidence for proving the main hypothesis in the previous section of the thesis.

Table 5.5 : EGARCH Results for S&P500: Different investor sentiment proxies.

coeff.	*VOLUME*	*PUT/CALL*	*AAII*	*VIX*	*BWURGLER*
θ_0	0.0008 (0.9421)	-0.0003 (-0.4647)	-0.0004 (-0.5155)	-0.0019 (-2.7183**)	0.0010 (1.1847)
θ_1	0.0000 (-5.6153**)	-0.0570 (-9.8651**)	-0.0142 (-3.1314**)	-0.0015 (-11.3359**)	-0.0029 (-1.648)
γ_0	-7.3108 (-5.7731**)	-0.7184 (-6.5173**)	-0.6547 (-5.3825**)	-0.8738 (-5.2411**)	-0.6374 (-5.5264**)
γ_1	0.0100 (0.1927)	0.1831 (4.845**)	0.1786 (4.7557**)	0.1908 (4.5722**)	0.1770 (5.2987**)
γ_2	0.0100 (0.2794)	-0.2030 (-9.1096**)	-0.2060 (-7.8578**)	-0.1814 (-7.558**)	-0.1819 (-9.2679**)
γ_3	0.0100 (0.0571)	0.9241 (71.1454**)	0.9316 (66.7982**)	0.9048 (44.3158**)	0.9346 (69.5913**)
γ_4	0.0000 (7.3367**)	0.4760 (6.2346**)	0.1605 (1.8802*)	0.0120 (5.1565**)	0.0290 (2.0885*)
R-squared	0.0178	0.0902	0.0132	0.0612	0.0043
Adjusted R-squared	0.0167	0.0891	0.0120	0.0601	0.0031
Akaike info criterion	-4.48002	-4.812994	-4.706701	-4.845465	-4.710371
Schwarz criterion	-4.4422	-4.7742	-4.6650	-4.8077	-4.6687
Hannan-Quinn criter.	-4.4656	-4.7981	-4.6907	-4.8310	-4.6943

After the verification of the main hypothesis with the S&P500 itself, the model is applied to the returns of the portfolios composed of all the stocks in the S&P500 sorted according to their market capitalization and book-to-market ratio. The market capitalization decreases and the book-to-market ratio increases from portfolio 1 to portfolio 5. The main claim of this section is that investor sentiment increases the variance of small stocks and growth stocks more than it does for big stocks and value stocks. Therefore, it is anticipated that the coefficient γ_4 increases from portfolio Cap 1 to portfolio Cap 5 as market capitalization decreases indicating a size effect. Additionally, γ_4 increases from portfolio Book 5 to portfolio Book 1 as book-to-market ratio decreases indicating a book-to-market effect. In other words, Cap 1 and Cap 5 stand for portfolios of big stocks and small stocks respectively, whereas Book 1 and Book 5 stand for portfolios of growth stocks and value stocks respectively.

Table 5.6 displays the descriptive statistics for the returns of the portfolios, which are sorted according to their market capitalization. A close examination of the means indicate that portfolio Cap 5 has experienced higher average return which confirms a size effect. All the portfolios' returns are negatively skewed pointing out to fatter tails extending to negative values. Jarque-Bera statistics show that the distributions of the returns are not normal.

Table 5.6 : Descriptive statistics of market capitalization sorted porftolio returns.

	CAP1	*CAP2*	*CAP3*	*CAP4*	*CAP5*
Mean	0.001087	0.001013	0.001582	0.002483	0.003988
Median	0.002713	0.002518	0.003382	0.003696	0.005795
Maximum	0.109314	0.121335	0.141414	0.170374	0.227362
Minimum	-0.202019	-0.223088	-0.218924	-0.213845	-0.193138
Std. Dev.	0.025418	0.025232	0.026914	0.027886	0.032177
Skewness	-0.790544	-1.14143	-0.948387	-0.764127	-0.265069
Kurtosis	9.238325	12.04098	10.35094	11.25547	10.57919
Jarque-Bera	1710.158	3590.342	2379.807	2910.578	2383.57
Probability	0	0	0	0	0
Sum	1.076763	1.003393	1.568126	2.460678	3.952148
Sum Sq. Dev.	0.639618	0.630273	0.717122	0.769852	1.025036

The descriptive statistics of the book-to-market value sorted porfolios' returns are presented in Table 5.7. The most important observation is that the growth stock porfolios have gained higher average returns indicating a book-to-market effect. Other characteristics are the same as the market capitalization sorted portfolios.

Table 5.7 : Descriptive statistics of book-to-market ratio sorted portfolio returns.

	BOOK1	*BOOK2*	*BOOK3*	*BOOK4*	*BOOK5*
Mean	0.003552	0.001046	0.00104	-0.00017	-0.001742
Median	0.004762	0.002292	0.002023	0.001931	0.000932
Maximum	0.096866	0.094807	0.110669	0.160707	0.242004
Minimum	-0.178402	-0.183769	-0.144981	-0.210813	-0.360273
Std. Dev.	0.026069	0.025323	0.025133	0.027768	0.034541
Skewness	-0.668604	-0.660403	-0.454546	-0.688495	-1.807206
Kurtosis	7.836525	7.641796	6.773133	9.913308	24.90692
Jarque-Bera	1039.728	961.716	621.9755	2051.78	20355.84
Probability	0	0	0	0	0
Sum	3.520096	1.036278	1.030362	-0.168937	-1.72648
Sum Sq. Dev.	0.672808	0.63482	0.625338	0.763325	1.181154

Table 5.8 displays the results of the Trading Volume proxy for size effect and it is clear that γ_4 is statistically significant and γ_4 increases as the market capitalization decreases (from cap 1 to cap 5). Table 5.9 shows the results of the Trading Volume proxy for book-to-market effect and γ_4 increases as the book-to-market ratio decreases (book 1 to book 5). These results provide evidence that the sentiment specifically increases the variance of small stocks and growth stocks more than it does for big stocks and value stocks when trading volume is chosen as sentiment proxy.

Table 5.8 : EGARCH model with Trading Volume proxy – Size effect.

coeff.	*CAP1*	*CAP2*	*CAP3*	*CAP4*	*CAP5*
θ_0	0.0011 (1.2754)	0.0011 (1.2801)	0.0016 (1.8218)	0.0025 (2.7229**)	0.0041 (3.8345**)
θ_1	-3.40E-12 (-5.9725**)	-3.08E-12 (-5.5696**)	-3.50E-12 (-5.6956**)	-3.66E-12 (-5.8506**)	-3.82E-12 (-5.5268**)
γ_0	-7.3282 (-4.9433**)	-7.3412 (-7.2991**)	-7.2135 (-7.0544**)	-7.1444 (-9.5343**)	-6.8574 (-7.5181**)
γ_1	0.0100 (0.2098)	0.0100 (0.214)	0.0100 (0.2073)	0.0100 (0.2541)	0.0100 (0.2663)
γ_2	0.0100 (0.3141)	0.0100 (0.2779)	0.0100 (0.285)	0.0100 (0.3442)	0.0100 (0.3485)
γ_3	0.01000 (0.0491)	0.01000 (0.0715)	0.01000 (0.0693)	0.01000 (0.0933)	0.01000 (0.0753)
γ_4	9.81E-11 (6.2487**)	1.16E-10 (7.5916**)	1.21E-10 (8.2042**)	1.48E-10 (10.2168**)	1.40E-10 (11.3331**)
R-squared	0.0210	0.0175	0.0191	0.0175	0.0140
Adjusted R-squared	0.0199	0.0164	0.0181	0.0165	0.0130
Akaike info criterion	-4.488602	-4.508248	-4.383998	-4.325691	-4.036464
Schwarz criterion	-4.4525	-4.4721	-4.3479	-4.2896	-4.0003
Hannan-Quinn crit.	-4.4748	-4.4945	-4.3702	-4.3119	-4.0227

Table 5.9 : EGARCH model with Trading Volume proxy – Book-to-Market effect.

coeff.	***BOOK1***	***BOOK2***	***BOOK3***	***BOOK4***	***BOOK5***
θ_0	0.0036 (4.2232**)	0.0010 (1.2247)	0.0010 (1.2457)	-0.0002 (-0.2562)	0.0003 (0.4991)
θ_1	-2.82E-12 (-5.1008**)	-2.86E-12 (-4.9631**)	-2.40E-12 (-4.2433**)	-3.14E-12 (-5.49**)	-1.69E-12 (-2.6429**)
γ_0	-7.2792 (-4.7826**)	-7.3378 (-2.5889**)	-7.3441 (-5.2589**)	-7.1452 (-3.6901**)	-0.4359 (-8.4595**)
γ_1	0.0100 (0.2795)	0.0100 (0.1885)	0.0100 (0.2153)	0.0100 (0.2616)	0.1623 (4.9026**)
γ_2	0.0100 (0.3222)	0.0100 (0.3097)	0.0100 (0.2924)	0.0100 (0.3518)	-0.1722 (-8.6877**)
γ_3	0.01000 (0.0482)	0.01000 (0.0258)	0.01000 (0.052)	0.01000 (0.0371)	0.95903 (143.0256**)
γ_4	9.80E-11 (5.1758**)	5.87E-11 (4.1663**)	7.52E-11 (4.5938**)	6.77E-11 (5.4358**)	3.15E-12 (0.3882)
R-squared	0.0138	0.0157	0.0108	0.0171	0.0095
Adjusted R-squared	0.0127	0.0147	0.0097	0.0160	0.0084
Akaike info criterion	-4.436582	-4.489141	-4.498303	-4.297303	-4.553079
Schwarz criterion	-4.4005	-4.4530	-4.4622	-4.2612	-4.5170
Hannan-Quinn crit.	-4.4228	-4.4754	-4.4845	-4.2835	-4.5393

Table 5.10 shows the results of the AAII proxy for size effect where it can clearly be seen that γ_4 increases from portfolio 1 to 5 with the market capitalization’s decrease. In Table 5.11, the last portfolio’s γ_4 coefficient is statistically insignificant and the effect increases from portfolio 1 to 5 as the book-to-market ratio decreases. These results are in line with both the Trading Volume outputs and the main hypothesis of this paper supporting that the variance of small stocks and growth stocks are more prone to an increase in the investor sentiment.

The results for the Baker & Wurgler sentiment indicator are presented in Table 5.12 and Table 5.13. It is evident that the effect of the sentiment on variance increases as the book-to-market ratio decreases (from book 1 to book 5) showing that growth stocks are more prone to an increase in the investor sentiment. Nevertheless, the effect of the market capitalization on the impact of investor sentiment is not clear when Baker & Wurgler indicator is chosen as a sentiment proxy.

The case is the similar to Baker & Wurgler proxy for the Put/Call Ratio indicator since it can be observed from the Table 5.14 and Table 5.15 the effect of the investor sentiment on the variance increases as the book-to-market ratio decreases (from book

1 to book 5) but the effect of the market capitalization is not clear. Table 5.16 and Table 5.17 presents the results of the EGARCH model applied with VIX as proxy. Although there is a decrease in portfolios Cap 5 and Book 1, it is obvious that there is an increase in the coefficient γ_4 as the size increase and book-to-market ratio decreases for VIX as proxy for investor sentiment.

All these results clearly point that there is a considerable difference in the effect of the investor sentiment on conditional variance in terms market capitalization and book-to-market ratio. Although the size effect on the impact of investor sentiment on variance is not clear for Baker & Wurgler and Put/Call Ratio proxies, it is reasonable to conclude that market capitalization and book-to-market ratio of the stock plays an important role in the investor sentiment-variance relationship. Five different investor sentiment indicators are employed and it is observed that a hike in the investor sentiment increases especially the conditional variance of small stocks and growth stocks.

Table 5.10 : EGARCH model with AAII proxy – Size effect.

coeff.	***CAP1***	***CAP2***	***CAP3***	***CAP4***	***CAP5***
θ_0	-0.0003 (-0.4319)	-0.0005 (-0.5924)	0.0001 (0.0958)	0.0009 (1.0036)	0.0024 (2.5393*)
θ_1	-1.38E-02 (-2.9525**)	-1.84E-02 (-4.0149**)	-1.83E-02 (-3.6076**)	-2.03E-02 (-4.0552**)	-2.50E-02 (-4.2639**)
γ_0	-0.6549 (-5.6946**)	-0.5887 (-6.2397**)	-0.5719 (-5.402**)	-0.7727 (-5.5335**)	-0.5540 (-4.621**)
γ_1	0.1815 (4.6479**)	0.1214 (3.4126**)	0.0967 (3.1642**)	0.1502 (4.433**)	0.1445 (4.2136**)
γ_2	-0.1995 (-8.3152**)	-0.2222 (-8.8264**)	-0.2101 (-8.858**)	-0.2008 (-7.9768**)	-0.1719 (-7.6694**)
γ_3	0.93183 (70.7278**)	0.93456 (87.9502**)	0.93258 (74.1148**)	0.91087 (52.9345**)	0.93760 (66.6592**)
γ_4	1.66E-01 (2.0423*)	1.75E-01 (2.2733*)	1.83E-01 (2.164*)	2.85E-01 (2.9607**)	2.32E-01 (2.8612**)
R-squared	0.0141	0.0200	0.0179	0.0194	0.0209
Adjusted R-squared	0.0129	0.0187	0.0166	0.0182	0.0196
Akaike info criterion	-4.679385	-4.723673	-4.560564	-4.536736	-4.264273
Schwarz criterion	-4.6377	-4.6820	-4.5189	-4.4950	-4.2226
Hannan-Quinn crit.	-4.6634	-4.7076	-4.5445	-4.5207	-4.2482

Table 5.11 : EGARCH model with AAII proxy – Book-to-Market effect.

coeff.	*BOOK1*	*BOOK2*	*BOOK3*	*BOOK4*	*BOOK5*
θ_0	0.0022 (2.776**)	-0.0006 (-0.6866)	-0.0009 (-1.0959)	-0.0014 (-1.7446)	-0.0018 (-2.2396*)
θ_1	-9.03E-03 (-1.9929*)	-1.29E-02 (-2.7466**)	-1.58E-02 (-3.4492**)	-1.82E-02 (-3.9077**)	-2.31E-02 (-5.097**)
γ_0	-0.6421 (-4.5885**)	-0.8991 (-5.8668**)	-0.7037 (-6.1504**)	-0.4571 (-8.8383**)	-0.3685 (-7.7397**)
γ_1	0.2766 (6.7812**)	0.1930 (4.1575**)	0.1219 (3.1708**)	0.0627 (2.553*)	0.0853 (2.5116*)
γ_2	-0.1081 (-4.2526**)	-0.2165 (-7.3117**)	-0.2254 (-8.4864**)	-0.2309 (-9.9461**)	-0.2076 (-9.5585**)
γ_3	0.94174 (58.4176**)	0.90012 (46.4194**)	0.91894 (67.151**)	0.94516 (135.2627**)	0.95893 (163.4771**)
γ_4	6.91E-02 (1.0267)	2.53E-01 (2.6256**)	2.29E-01 (2.8525**)	2.11E-01 (2.9341**)	1.47E-01 (2.2445*)
R-squared	0.0065	0.0073	0.0135	0.0176	0.0252
Adjusted R-squared	0.0052	0.0060	0.0122	0.0164	0.0240
Akaike info criterion	-4.575789	-4.654466	-4.694461	-4.568195	-4.386758
Schwarz criterion	-4.5341	-4.6128	-4.6528	-4.5265	-4.3451
Hannan-Quinn crit.	-4.5598	-4.6384	-4.6784	-4.5522	-4.3707

Table 5.12 : EGARCH model with Baker&Wurgler proxy – Size effect.

coeff.	*CAP1*	*CAP2*	*CAP3*	*CAP4*	*CAP5*
θ_0	0.0014 (2.0814*)	0.0014 (2.0556*)	0.0018 (2.485*)	0.0029 (3.9889**)	0.0042 (5.0669**)
θ_1	-3.20E-03 (-1.8218)	-2.37E-03 (-1.575)	-1.82E-03 (-1.2114)	-1.40E-03 (-0.9753)	-1.88E-03 (-1.2358)
γ_0	-0.5955 (-5.7972**)	-0.5703 (-6.7999**)	-0.5089 (-8.0847**)	-0.6156 (-6.7224**)	-0.5807 (-5.975**)
γ_1	0.1877 (5.6578**)	0.1466 (5.026**)	0.1075 (3.8741**)	0.1561 (5.0761**)	0.2057 (5.7678**)
γ_2	-0.1544 (-8.4792**)	-0.1773 (-9.91**)	-0.1750 (-9.5293**)	-0.1763 (-9.182**)	-0.1429 (-7.2479**)
γ_3	0.94203 (80.7318**)	0.94158 (99.2321**)	0.94430 (137.4207**)	0.93500 (86.6955**)	0.94271 (85.4913**)
γ_4	3.69E-02 (2.9182**)	3.08E-02 (2.5512*)	2.59E-02 (2.6221**)	2.82E-02 (2.7875**)	2.95E-02 (2.8503**)
R-squared	0.0062	0.0030	0.0008	0.0001	0.0007
Adjusted R-squared	0.0051	0.0019	-0.0004	-0.0011	-0.0004
Akaike info criterion	-4.813555	-4.871075	-4.744694	-4.687208	-4.423164
Schwarz criterion	-4.7757	-4.8333	-4.7069	-4.6494	-4.3853
Hannan-Quinn crit.	-4.7991	-4.8566	-4.7302	-4.6728	-4.4087

Table 5.13 : EGARCH model with Baker&Wurgler proxy – Book-to-Market effect.

coeff.	*BOOK1*	*BOOK2*	*BOOK3*	*BOOK4*	*BOOK5*
θ_0	0.0036 (4.7435**)	0.0011 (1.5178)	0.0011 (1.583)	0.0005 (0.6671)	0.0002 (0.2544)
θ_1	-3.45E-03 (-1.8517)	-3.97E-03 (-2.1853*)	-2.52E-03 (-1.5146)	-1.71E-03 (-0.9497)	-2.18E-03 (-1.4348)
γ_0	-0.8353 (-4.725**)	-0.9132 (-5.7352**)	-0.7192 (-6.2355**)	-0.4832 (-7.793**)	-0.3707 (-7.493**)
γ_1	0.2601 (6.7132**)	0.2166 (5.3689**)	0.1649 (4.6226**)	0.1321 (4.6019**)	0.1552 (5.0937**)
γ_2	-0.0837 (-4.0631**)	-0.1700 (-6.9968**)	-0.1757 (-8.0367**)	-0.1737 (-9.2724**)	-0.1465 (-8.2378**)
γ_3	0.91544 (42.9828**)	0.90247 (46.4531**)	0.92309 (68.7577**)	0.95043 (128.6591**)	0.96744 (161.1871**)
γ_4	5.41E-02 (2.5547*)	4.98E-02 (2.9696**)	3.28E-02 (2.4528*)	3.11E-02 (2.4448*)	2.68E-02 (3.034**)
R-squared	0.0064	0.0084	0.0033	0.0020	-0.0012
Adjusted R-squared	0.0053	0.0073	0.0022	0.0009	-0.0024
Akaike info criterion	-4.609283	-4.718454	-4.784037	-4.704456	-4.641686
Schwarz criterion	-4.5715	-4.6806	-4.7462	-4.6666	-4.6039
Hannan-Quinn crit.	-4.5948	-4.7040	-4.7696	-4.6900	-4.6272

Table 5.14 : EGARCH model with Put/Call Ratio – Size effect.

coeff.	*CAP1*	*CAP2*	*CAP3*	*CAP4*	*CAP5*
θ_0	-0.0002 (-0.3)	0.0003 (0.361)	0.0004 (0.501)	0.0012 (1.514)	0.0027 (3.24**)
θ_1	-5.56E-02 (-9.312**)	-5.42E-02 (-9.529**)	-6.24E-02 (-10.975**)	-6.13E-02 (-10.357**)	-7.46E-02 (-12.004**)
γ_0	-0.7187 (-6.327**)	-0.6312 (-7.463**)	-0.3701 (-6.963**)	-0.4647 (-6.863**)	-0.4319 (-5.355**)
γ_1	0.1962 (4.777**)	0.1450 (4.85**)	0.0476 (1.743)	0.0906 (3.273**)	0.1452 (4.328**)
γ_2	-0.1913 (-8.75**)	-0.1948 (-10.38**)	-0.1927 (-10.818**)	-0.1886 (-10.504**)	-0.1571 (-8.116**)
γ_3	0.92518 (68.68**)	0.93222 (90.826**)	0.95516 (153.876**)	0.94678 (120.069**)	0.95548 (109.21**)
γ_4	4.78E-01 (6.516**)	4.67E-01 (6.839**)	4.48E-01 (7.68**)	4.68E-01 (7.803**)	4.43E-01 (8.183**)
R-squared	0.0854	0.0803	0.0853	0.0807	0.0845
Adjusted R-squared	0.0843	0.0792	0.0842	0.0797	0.0834
Akaike info criterion	-4.768703	-4.831166	-4.719619	-4.670346	-4.414129
Schwarz criterion	-4.7299	-4.7923	-4.6808	-4.6315	-4.3753
Hannan-Quinn crit.	-4.7538	-4.8163	-4.7048	-4.6555	-4.3993

Table 5.15 : EGARCH model with Put/Call Ratio – Book-to-Market effect.

coeff.	***BOOK1***	***BOOK2***	***BOOK3***	***BOOK4***	***BOOK5***
θ_0	0.0023 (3.026**)	-0.0006 (-0.7699)	-0.0005 (-0.6847)	-0.0009 (-1.279)	-0.0006 (-0.8647)
θ_1	-5.33E-02 (-8.6025**)	-5.72E-02 (-9.6527**)	-5.58E-02 (-9.2895**)	-5.17E-02 (-8.4042**)	-4.97E-02 (-8.0285**)
γ_0	-0.7858 (-5.3766**)	-1.0762 (-6.9814**)	-0.9016 (-6.627**)	-0.5238 (-8.5475**)	-0.3992 (-6.8156**)
γ_1	0.2858 (7.566**)	0.2279 (4.8496**)	0.2168 (4.7503**)	0.1356 (5.0048**)	0.1393 (3.8451**)
γ_2	-0.1504 (-6.0852**)	-0.2086 (-7.2872**)	-0.1912 (-7.4727**)	-0.2048 (-10.262**)	-0.1537 (-8.8585**)
γ_3	0.92353 (51.7307**)	0.88061 (45.2764**)	0.90352 (54.5604**)	0.94390 (119.3596**)	0.96092 (147.6452**)
γ_4	1.35E-01 (1.8047)	7.66E-01 (7.3592**)	6.80E-01 (6.6994**)	5.25E-01 (7.6048**)	4.44E-01 (6.7704**)
R-squared	0.0776	0.0750	0.0729	0.0639	0.0519
Adjusted R-squared	0.0765	0.0739	0.0718	0.0628	0.0508
Akaike info criterion	-4.619463	-4.723492	-4.765154	-4.641425	-4.527782
Schwarz criterion	-4.5806	-4.6847	-4.7263	-4.6026	-4.4890
Hannan-Quinn crit.	-4.6046	-4.7086	-4.7503	-4.6266	-4.5129

Table 5.16 : EGARCH model with VIX – Size effect.

coeff.	***CAP1***	***CAP2***	***CAP3***	***CAP4***	***CAP5***
θ_0	-0.0008 -1.3512	-0.0006 -1.0807	-0.0002 -0.3209	0.0004 0.5694	0.0013 1.6971
θ_1	-1.48E-03 -11.7**	-1.43E-03 -11.8569**	-1.54E-03 -11.8778**	-1.63E-03 -12.0886**	-2.01E-03 -14.4947**
γ_0	-0.6596 -5.6729**	-0.7740 -6.8583**	-0.7762 -6.8344**	-1.0086 -5.8985**	-0.7354 -5.9654**
γ_1	0.1908 4.8622**	0.1663 4.5854**	0.1328 3.5473**	0.1663 4.1906**	0.1666 4.6374**
γ_2	-0.1572 -7.7186**	-0.1778 -8.5003**	-0.1707 -7.9197**	-0.1854 -7.7262**	-0.1563 -7.4015**
γ_3	0.93372 69.6043**	0.91740 64.7473**	0.91205 64.6677**	0.88453 40.8858**	0.91749 57.817**
γ_4	8.81E-03 5.1957**	1.03E-02 5.2376**	1.08E-02 5.6904**	1.35E-02 5.312**	1.16E-02 5.6528**
R-squared	0.0794	0.0901	0.0990	0.0905	0.0644
Adjusted R-squared	0.0785	0.0892	0.0981	0.0896	0.0634
Akaike info criterion	-4.930606	-4.987388	-4.850836	-4.804382	-4.540485
Schwarz criterion	-4.8960	-4.9528	-4.8162	-4.7698	-4.5059
Hannan-Quinn crit.	-4.9174	-4.9742	-4.8377	-4.7912	-4.5273

Table 5.17 : EGARCH model with VIX – Book-to-Market effect.

coeff.	*BOOK1*	*BOOK2*	*BOOK3*	*BOOK4*	*BOOK5*
θ_0	0.0018	-0.0010	-0.0008	-0.0015	-0.0016
	2.6452**	-1.5276	-1.2157	-2.4764*	-2.615**
θ_1	-1.24E-03	-1.38E-03	-1.36E-03	-1.48E-03	-1.65E-03
	-10.0175**	-11.3801**	-10.4823**	-11.3481**	-11.8263**
γ_0	-0.5044	-0.8881	-0.8382	-0.5908	-0.5052
	-4.5988**	-5.5015**	-5.6224**	-7.2304**	-7.6947**
γ_1	0.2291	0.2161	0.1517	0.1426	0.1738
	6.7233**	4.8017**	3.922**	4.0531**	4.9911**
γ_2	-0.0851	-0.1734	-0.1731	-0.1787	-0.1577
	-5.0243**	-7.3086**	-7.1047**	-8.9968**	-9.0132**
γ_3	0.95607	0.90557	0.90637	0.93721	0.95151
	74.9752**	45.4689**	49.0383**	89.0109**	109.4832**
γ_4	3.89E-03	9.94E-03	1.08E-02	9.15E-03	7.08E-03
	2.7577**	5.0083**	5.2171**	5.4608**	4.3006**
R-squared	0.0496	0.0493	0.0667	0.0909	0.1238
Adjusted R-squared	0.0487	0.0484	0.0658	0.0899	0.1230
Akaike info criterion	-4.703545	-4.832313	-4.886969	-4.830713	-4.71572
Schwarz criterion	-4.6689	-4.7977	-4.8523	-4.7961	-4.6811
Hannan-Quinn crit.	-4.6904	-4.8191	-4.8738	-4.8175	-4.7026

The figures in the Appendix section (see Appendix A) represent the changes of the impact of investor sentiment for portfolios, which have been sorted according to market capitalization and book-to-market ratio. The corresponding figures representing the changes in the coefficient γ_4 as the observations goes from portfolio 1 to portfolio 5 show that market capitalization and book-to-market ratio has a considerable effect on the investor sentiment-conditional volatility relationship where the impact is greater for small stocks and growth stocks. Even though the above tables and the corresponding figures provide formidable evidence of a relationship between a size or book-to-market premium and conditional volatility, it should also be explored whether this difference in the magnitude of the effect of the investor sentiment represented by the coefficient γ_4 is statistically significant. The Wald tests showed that the differences in the magnitude of the effect of the investor sentiment between big stock small and small stock portfolios; as well as growth stock and value stock portfolios are not statistically significant despite being considerable and observable. This lack of statistical significance might be due to the long interval of observation chosen in the study since these types of anomalies disappear in the long term due to the presence of the arbitrageurs in the market.

5.3 The effects of investor sentiment for different economic sectors: Evidence from Istanbul Stock Exchange

The descriptive statistics of the returns for sector indices of BIST has been presented in Table 5.18. Banking sector experienced the highest average returns.

Table 5.18 : Descriptive statistics of the returns for sector indices of ISE.

	RETAIL	*TELCOM*	*TEXTILE*	*SERVICE*	*FOOD&BEV*	*BANKS*	*INDUSTRY*
Mean	0.0047	0.0032	0.0021	0.0036	0.0040	0.0048	0.0035
Median	0.0048	0.0009	0.0046	0.0050	0.0033	0.0059	0.0063
Maximum	0.2793	0.1625	0.1702	0.1643	0.1251	0.3656	0.2118
Minimum	-0.2351	-0.1422	-0.2255	-0.1310	-0.1720	-0.2059	-0.2012
Std. Dev.	0.0391	0.0481	0.0387	0.0335	0.0400	0.0535	0.0366
Skewness	0.0810	0.1328	-0.8665	-0.0155	-0.3205	0.4261	-0.5855
Kurtosis	10.2952	3.6675	7.0251	4.9469	4.8645	7.6215	7.5889
Jarque-Bera	1,206.91	11.70	435.30	85.93	88.11	500.59	508.39
Probability	0.0000	0.0029	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	2.5707	1.7246	1.1162	1.9739	2.1751	2.6049	1.8904
Sum Sq. Dev.	0.8315	1.2545	0.8116	0.6101	0.8675	1.5539	0.7272

Banking sector also has a high positive skewness which indicates a distribution with an asymmetric tail extending to positive values meaning a few past extreme gains and frequent past small losses.

The main EGARCH model has been modified to better fit the data and $\Delta Sent_{t-1}$ has been used in the model instead of $Sent_{t-1}$ since it was observed that the coefficient for $Sent_{t-1}$ in the first study was not statistically significant for BIST100 returns. The change in the sentiment indicator rather than the level of the indicator has been used in the main EGARCH model where the momentum in the investor sentiment is significant.

Table 5.19 gives the summary of the EGARCH model applied to the returns of ISE sector indices. It is found that γ_2 is negative and statistically significant for most of the sector indices indicating there is negative leverage effect. Higher and statistically significant γ_3 coefficients for Industry, Banks, Telecommunications, and Textile indices also demonstrate that there is high persistence in volatility which points that long-term variance might be modelled separately for further inspection among these sectors. As expected, the coefficients γ_4 are positive and statistically significant for all the sector indices pointing that an increase in the investor sentiment, which means higher participation of noise traders, increases the conditional volatility consistent with the noise trader theory.

Table 5.19 : EGARCH model results ISE Sector Indices.

coeff.	*RETAIL*	*TELCOM*	*TEXTILE*	*SERVICE*	*FOOD&BEV*	*BANKS*	*INDUSTRY*
θ_0	0.0036 (2.531*)	0.0024 (1.363)	0.0022 (1.405)	0.0021 (1.558)	0.0031 (1.881)	0.0034 (1.8)	0.0024 (1.707)
γ_0	-8.7036 (-26.571**)	-0.0524 (-1.925)	-1.0059 (-3.789**)	-4.3105 (-4.574**)	-6.0904 (-6.047**)	-0.3739 (-2.679**)	-2.2084 (-6.134**)
γ_1	0.4737 (7.419**)	0.0519 (2.596**)	0.2310 (3.884**)	0.1589 (1.649)	0.1901 (2.172*)	0.1688 (3.366**)	0.1008 (1.451)
γ_2	-0.1191 (-2.4*)	0.0060 (0.302)	-0.0965 (-4.485**)	-0.2249 (-3.646**)	-0.0792 (-1.465)	-0.0710 (-2.837**)	-0.2637 (-6.188**)
γ_3	-0.25835 (-5.065**)	0.99876 (332.459**)	0.87445 (24.17**)	0.39334 (2.937**)	0.08735 (0.58)	0.96032 (45.929**)	0.68696 (13.838**)
γ_4	7.95E-05 (4.304**)	8.39E-05 (3.402**)	1.31E-04 (6.441**)	1.56E-04 (6.029**)	1.73E-04 (6.053**)	2.04E-04 (9.903**)	2.17E-04 (11.444**)
R-squared	-0.0006	-0.0002	0.0000	-0.0018	-0.0004	-0.0005	-0.0007
Adjusted R-squared	-0.0006	-0.0002	0.0000	-0.0018	-0.0004	-0.0005	-0.0007
Akaike info criterion	-3.775845	-3.383037	-3.794541	-4.047167	-3.660374	-3.19169	-3.961475
Schwarz criterion	-3.7284	-3.3356	-3.7471	-3.9997	-3.6129	-3.1442	-3.9140
Hannan-Quinn criter.	-3.7573	-3.3645	-3.7760	-4.0286	-3.6418	-3.1731	-3.9429

A close examination of the coefficient γ_4 among the indices suggests that a hike in the investor sentiment causes a larger increase in the conditional volatility of some of the sectors. The conditional volatility of industry and banking sector indices are the most vulnerable ones against an increase in the investor sentiment while the conditional volatility of retail and telecommunication sector indices are the least effected. Figure 5.1 below shows a representation of the impact of the investor sentiment assuming that the impact for retail sector index (the lowest) is 100.

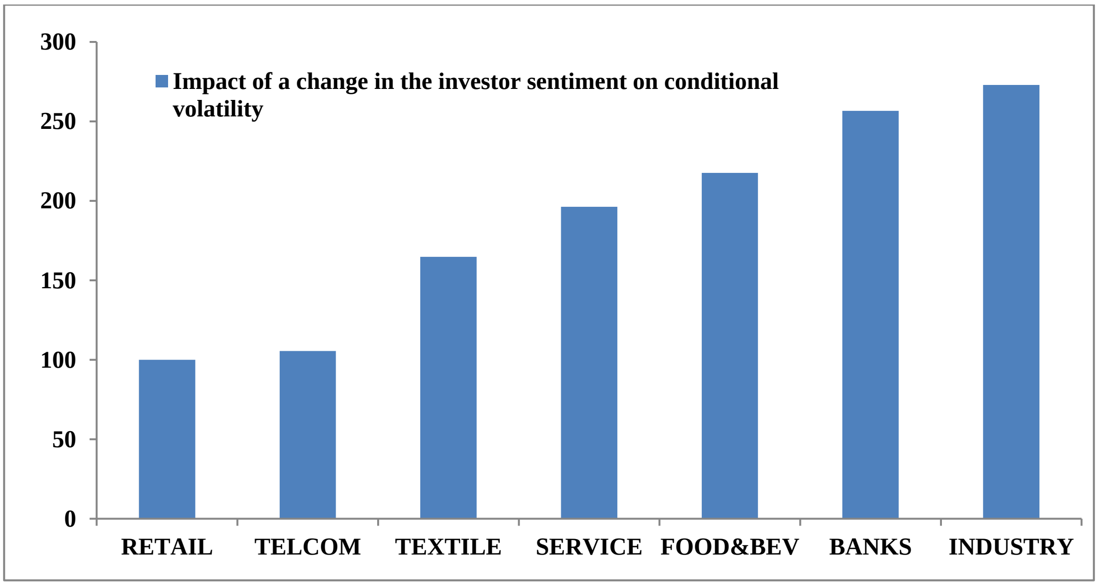

Figure 5.1 : Representation for the impact of investor sentiment.

ISE30 index is comprised of the stocks which are most closely monitored and mostly traded both by institutional and individual traders and ISE30 is mostly made up of Banking and Industrial stocks where their weights in the index are relatively high compared to other sectors. Moreover, a close examination of the average free float market capital of these seven sector indices reveals that industry and banking sectors have the highest free float market capital relative to other sectors creating an additional trading availability for both institutional and individual players in the market. Foreign clearing data obtained from FINNET also showed that stocks in banking and industry sectors are the prominent traded stocks in the ISE among the foreign investors where both individual and institutional investors in the ISE market watch closely the trading activities of the foreign investors.

Noise traders are naïve players whose buying and selling decisions do not base on the use of fundamental data. Their timing is poor and they follow trends, and over-react to good and bad news. All these circumstances regarding the industry and banking sectors make them the key driving sectors that lead the ISE and cause noise (sentiment) traders to consider them favorable and monitor them closely. The results of the EGARCH model showed that a rise in the investor sentiment leads to a bigger increase in the conditional volatility of Industry and Banking sectors. On account of the fact that the noise traders are always monitoring the price movements of equities and listening to other conditions of the stock market, these findings are logical and in line with the noise trader theory because noise traders' enduring activity of buys and sells puts pressures on the prices and increase the volatility. As a result, the conditional volatility of banking and industry sectors are more prone to the changes in the investor sentiment.

The difference between the coefficients γ_4 for the sector indices should also be evaluated to clarify whether the magnitude of the differences between the impact of investor sentiment on conditional volatility on these sectors are also statistically significant. The Wald test (Table 5.20) showed that the differences between γ_4 coefficients are also statistically significant (marginally for 5%) proving that the impact of a change in investor sentiment on the conditional volatility is not only arithmetically greater for Banking and Industry stocks but also statistically meaningful.

Table 5.20 : Wald Test for statistical significance for sector indices.

Wald Test:
Equation: EQ01

Test Statistic	Value	df	Probability
t-statistic	1.854197	1080	0.0640
F-statistic	3.438047	(1, 1080)	0.0640
Chi-square	3.438047	1	0.0637

Null Hypothesis: C(7)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(7)	3.38E-05	1.82E-05

Restrictions are linear in coefficients.

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6. CONCLUSIONS AND RECOMMENDATIONS

The conclusions section of the thesis is divided into three parts since there are three separate but interconnected hypotheses in the study. The first section discusses the results of the main EGARCH model applied to the nine different stock market indices where an international approach is adopted. The first hypothesis suggested that an increase in the investor sentiment would decrease the returns and increase the conditional volatility due to the higher participation of noise traders in the market. The analysis regarding the first hypothesis gives a general understanding of the investor sentiment-conditional variance relationship and serves as a foundation for further research concerning the effects of the investor sentiment in stock markets.

The second section of the conclusions part provides insights regarding the analyses for the second hypothesis where a different point of view from the first part is taken. The claim of the second hypothesis is that an increase in the investor sentiment causes a greater increase in the conditional volatility of growth stocks and small stocks. In contrast to the first part of the thesis, the second part explored the investor sentiment-conditional volatility relationship on an individual stock level. The findings in the second part of the thesis provided better insights about the impacts of the investor sentiment on stock markets focusing not only on the main stock market indices but also the stocks that constitute those indices in the first place.

The last part of the conclusions is dedicated to the analyses concerning the different impacts of the investor sentiment on stocks from different economic sectors. Depending on the noise trader approach, it has been expected that the conditional volatility of the stocks from banking and industry sectors would be more prone to the changes in the investor sentiment. The main differences of the analyses in this part of the thesis than the previous parts are the alterations in the main EGARCH model and the choice of the dependent variable used in the model. The sentiment in the mean equation is omitted and the investor sentiment in the variance equation is superseded with ‘the change in the investor sentiment’. These changes in the model have been implemented to better fit not only the hypothesis but also the dependent variables chosen: The returns of various sector indices from Istanbul Stock Exchange.

6.1 Conclusions regarding Hypothesis - I

EGARCH model is employed in order to evaluate the weekly returns of 9 different market indexes and their conditional volatility considering the changes in the investor sentiment. Weekly trading volume data of these market indexes are used for constructing a new investor sentiment measure by regressing the trading volume against a set of various macroeconomic variables such as Industrial Production, Producers Price Index, Consumers Price Index, Gross Domestic Product, Capacity Utilization Rate, Money Supply, Long Term Interest Rate and taking the residuals of these regression analysis as a proxy for investor sentiment.

It is observed that there is a strong relationship between investor sentiment and market returns. Higher investor sentiment has a negative effect on returns putting pressure on the prices because noise traders participate more during high sentiment periods. Excepts for the BIST100, NIKKEI, and HSI market indexes, the investor sentiment has a negative and significant impact on market returns.

It is examined that there is asymmetric volatility for ISE, DAX, CAC, HSI indices meaning that there is negative leverage effect. Thus, bad news (negative earning shocks) leads to more volatility than good news does (positive earning shocks) in these stock markets. This also indicates that there is no long term asymmetric volatility in other five stock market indices when the effects of the investor sentiment are controlled. The persistence of these stock market indices is also investigated in this part of the research. High and significant persistence points out that volatility takes a long time to die out following a crisis in the market. Similar to the asymmetric volatility case, the results demonstrated that BIST, DAX, CAC, HSI stock market indices seem to show high persistence which might be indicating a problem for long-term modelling and forecasting. A different kind of method such as component GARCH might be proposed in order to model the long term variance.

The study provided significant evidence that there is an asymmetric impact of the investor sentiment on the conditional volatility of the market index returns. A rise in the investor sentiment during low sentiment periods decreases the volatility whereas it increases the conditional volatility during high sentient periods. Among all the markets, it is discovered that the mean–variance relationship is weakened during high sentiment periods as suggested by the noise trader theory since an increase in the investor sentiment during high sentiment terms increases the volatility while it affects the returns negatively. This situation undermines the conservative risk-return relationship where investors get more returns when they take more risks, on the other hand, when there is persistent participation of noise traders in the market, the investors might end up with lower returns even though there is high volatility observed in the market.

For further study, the returns and volatility of the individual stocks that compose these particular market indexes should be also investigated considering the changes in the investor sentiment because investor sentiment might have a different effect on each stock according to their features. The sensitivity of these market indices might also be examined and the volatility spillovers between the stock markets might be modeled regarding the changes in the investor sentiment taking an international approach where multivariate GARCH models might be employed to investigate further effects of the investor sentiment. An interconnected model might be proposed to explore whether the sentiment of the developed stock markets (U.S., U.K., Germany etc.) have an effect on the sentiment of emerging stock markets (Turkey, Poland, South Africa etc.). A separate analysis might be carried out to have better insights if there is a pattern for specifically the developed markets or the emerging markets considering the long term effects of the investor sentiment on conditional volatility.

6.2 Conclusions regarding Hypothesis – II

The presence of the noise traders in the market ensures that investor sentiment would also play an important role in the asset pricing of the assets. Naive and inexperienced noise traders are more likely to miscalculate risk and thus, to miscalculate the variance of returns which undermines the mean-variance relation. Before exploring the impacts of investor sentiment on individual stock basis, five different investor sentiment proxies have been used in order to test whether the previously found sentiment-volatility relationship holds not only for the trading volume proxy but also for other investor sentiment proxies widely used in the literature. The weekly returns of the S&P500 have been used as dependent variables and the residuals from the controlling regressions of five different investor sentiment indicators have been used as exogenous variables in the variance equation of the main EGARCH model. As suggested by the noise trader theory, it is found for all the investor sentiment proxies used in the research that the mean-variance relationship is weakened as the investor sentiment increases since an increase in the investor sentiment increases the volatility of S&P 500 while it lowers the returns. Asymmetric volatility is observed in S&P 500 for all the sentiment proxies except for Trading Volume which means that there is negative leverage effect. Thus, bad news (negative earning shocks) leads to more volatility than good news (positive earning shocks). It is also indicated that there is high persistence in volatility for S&P500; hence there might be a need to use a component ARCH model instead of EGARCH in order to model the long term variance. These analyses have provided significant evidence that the impacts of the investor sentiment on conditional variance-return relationship holds also for other chosen investor sentiment proxies supporting the first hypothesis of the thesis.

This thesis have proposed an EGARCH model to evaluate the adverse effects of the investor sentiment specifically addressing the issues on stock level rather than focusing entirely on stock market indexes. Many of the previous studies focused solely on stock market indexes and fail to address the impacts of investor sentiment for stocks with different preferences. On the other hand, this study put more emphasis on the variance side of the relation investigating whether an escalation in the investor sentiment causes a more serious increase the variance of the stocks with small market capitalization and stocks with low book-to-market ratio (growth stocks) which are harder to value and arbitrage. Using the returns of the stocks in the S&P 500, it is determined that market capitalization and book-to-market ratio has a considerable effect on the investor sentiment – conditional variance relationship. Instead of using only one sentiment proxy like previous studies, this research utilized four different investor sentiment proxies and provided evidence that a rise in the investor sentiment especially increases the conditional variance of small stocks (size effect) and growth stocks (book-to-market effect). Using different kinds of investor sentiment proxies has provided an advantage to this research which proved useful both for comparison and verification purposes.

The magnitude of the difference of investor sentiment's effect on the conditional volatility among the portfolios has also been investigated. Although the differences between the impacts of investor sentiment among the portfolios are considerable and observable, there is no statistical significance both for size effect and book-to-market effect. The rationale behind the absence of statistical significance might be the fact that the observation period of the study has been a considerably long one of 18 years. It has been duly noted in literature that these kinds of anomalies disappear in the long run because of the presence of the arbitrageurs in the market. The data set of the study might be divided into subparts where this sentiment-conditional volatility relationship ought to be explored more properly. For further study, the investor sentiment could also be investigated in terms of other stock market anomalies like low P/E effect, low volatility effect or calendar effects to have a better understanding about the noise trader behavior. Other time series methods like frequency analysis could also be used in order to make trend and seasonality analysis due to the changes in the investor sentiment to study different time spans of the data.

6.3 Conclusions regarding Hypothesis – III

The main stock market indexes were the primary focus of all the earlier studies concerning the adverse effects of investor sentiment on stock markets without articulating about the impacts on different economic sectors. In addition to those researches, this paper provides a complimentary interpretation about the noise trader approach by inspecting the effects of noise traders on the conditional volatility of stock market indexes of different economic sectors in Istanbul Stock Exchange. Instead of using survey data or other sentiment indexes, a sentiment proxy is constructed by using ISE trading volume in order to capture the effects of investor sentiment on the returns and conditional volatility of stock markets.

In light of the findings in this thesis, it is duly noted that investor sentiment affects mostly the conditional volatility of the key driving sectors of the Turkish economy and Istanbul Stock Exchange: Industry and Banking sectors. The most traded and most closely watched index in Istanbul Stock Exchange is ISE30 which is more or less comprised of stocks from banking and industry sectors. Additionally, industry and banking sectors have the highest free float market capital relative to other sectors creating an additional trading availability for both institutional and individual players in the market. Foreign trading activity is closely monitored by all traders in ISE and it is also stronger in banking and industry stocks. Considering all these arguments, it is logical to infer that the industry and banking sectors would be more favorable for noise traders who follow trends, and over-react to good and bad news. Sentiment traders trust other traders'' trading activities do not depend on fundamental data and put pressure on the prices which increase the volatility. So, the implications of the EGARCH model regarding the industry and banking sector indexes' conditional volatility is in line with the noise trader theory since the increasing presence of noise trader activity in the respective sector index would mean additional risk hence volatility.

Although the results of the model suggested that economic sector affiliation of a stock might play an important role regarding its conditional volatility's vulnerability against the changes in the investor sentiment hence the increased presence of noise trader activity, there might also be present other latent factors that affect the relationship of conditional volatility and investor sentiment. It must be noted that stocks belonging to specific sectors share specific characteristics such as size, book-to-market ratio, dividend payout policy etc. It is evident that sector affiliation makes industry and banking stocks more favorable for noise traders in Istanbul Stock Exchange, a more comprehensive study might be carried out in order to understand whether the results of this study could be generalized for other stock markets and whether there are latent factors other than sector affiliation which alters the interaction between the conditional volatility and investor sentiment.

By increasing the financial literacy among individual traders in Turkey through awareness and education programs, the number of informed traders can be increased, thus the effect of the noise traders on volatility can be reduced. Additional IPO's (Initial Public Offering) and SPO's (Secondary Public Offering) would provide market depth and increase availability both for individual and institutional investors. These policy implications can reduce the pressure of the noise traders and investor sentiment on the prices and volatility of the Istanbul Stock Exchange improving the risk-reward tradeoff relation. Recent developments suggest that Istanbul Stock Exchange has been carrying out these aforementioned policies and has been actually trying to increase the efficiency in Turkish Financial Markets, and consequently, reduce the adverse effects of noise traders.

Recent developments and financial crises in the markets have leaded risk management to have the utmost importance in financial service industry. The particular interest arises from the sectors such as investment banking, commercial banking, and insurance companies and both interest and capability in risk management are broadening swiftly. While the governments try to establish risk based capital adequacy standards, the interest for risk management have become an essential element in regulatory policies. As a result of these developments risk management has become a standalone industry on its own attracting the attention of both industry professionals and academics. Dynamic risk management approaches have been developed with the improvements in computational simulation sciences and advances in volatility modeling. The main argument for risk management is that whether volatility could be forecasted and the risk-reward relationship could be explained.

The model proposed in this thesis could be employed for volatility forecasting and risk management purposes. The EGARCH model in this thesis tries to explain the conditional volatility of stock markets by taking into account not only the macro economic shocks but also the noise trader demand shocks. Including the investor sentiment in the model enables the forecaster to consider also the psychological aspects of the market while other models only focus on the price movements. Nonetheless, predictability of volatility changes a great deal with horizon of the observation since different risk management applications would require different horizons. It has been observed in the literature that the predictability for volatility weakens as the horizon widens. Since it has been determined that in order to get more insightful results the dataset should have been divided into sub parts and examined separately. These findings suggest that although the conditional volatility could be forecasted, the predictive powers are still short sighted and might only serve for short term investments.

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APPENDICES

APPENDIX A: Figures representing the changes of the impact of investor sentiment for portfolios.

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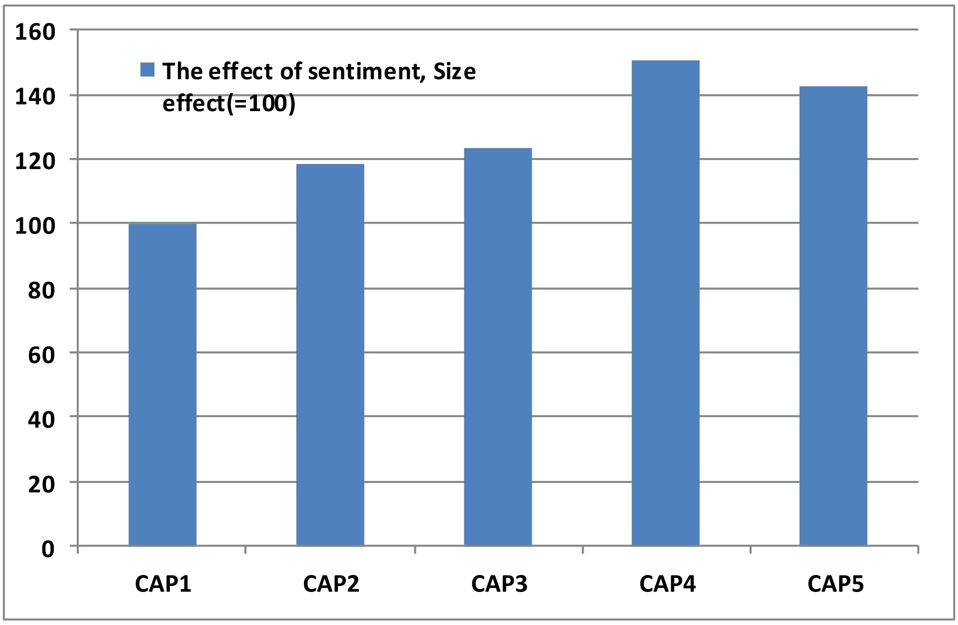

Figure A.1 : The impact of investor sentiment - Trading Volume proxy – Size effect.

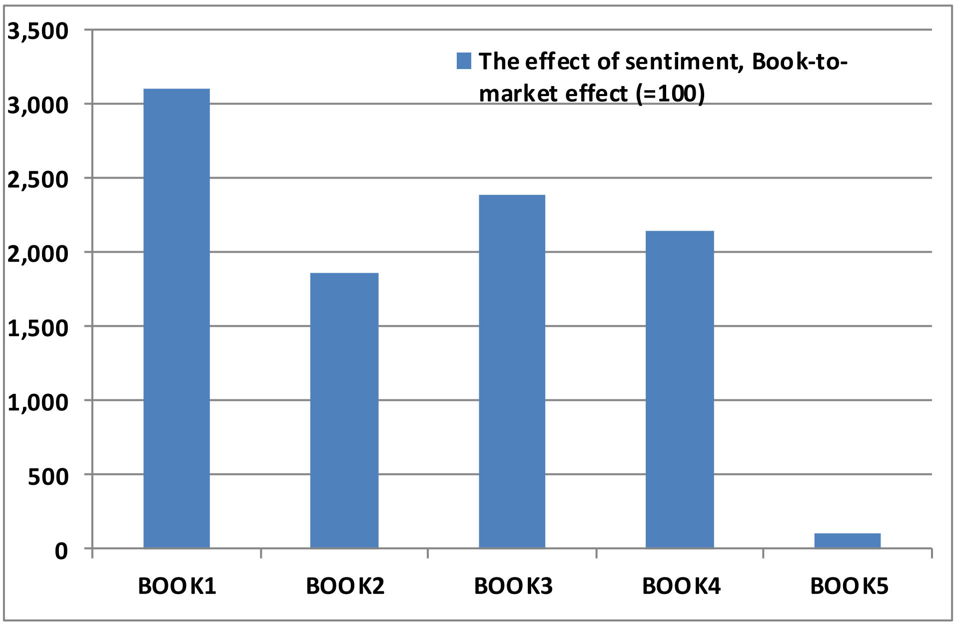

Figure A.2 : The impact of investor sentiment - Trading volume proxy – Book-to-market effect.

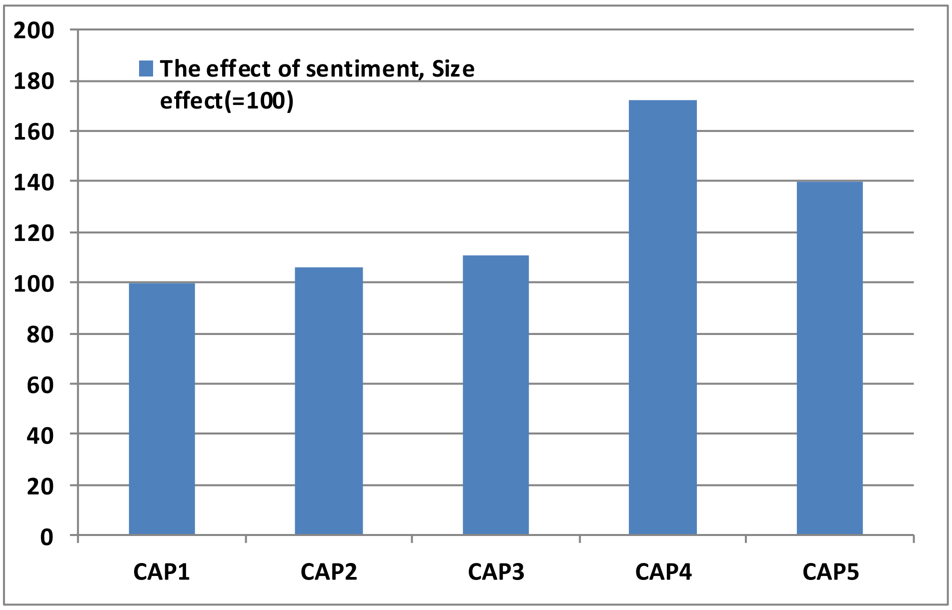

Figure A.3 : The impact of investor sentiment - AAII proxy – Size effect.

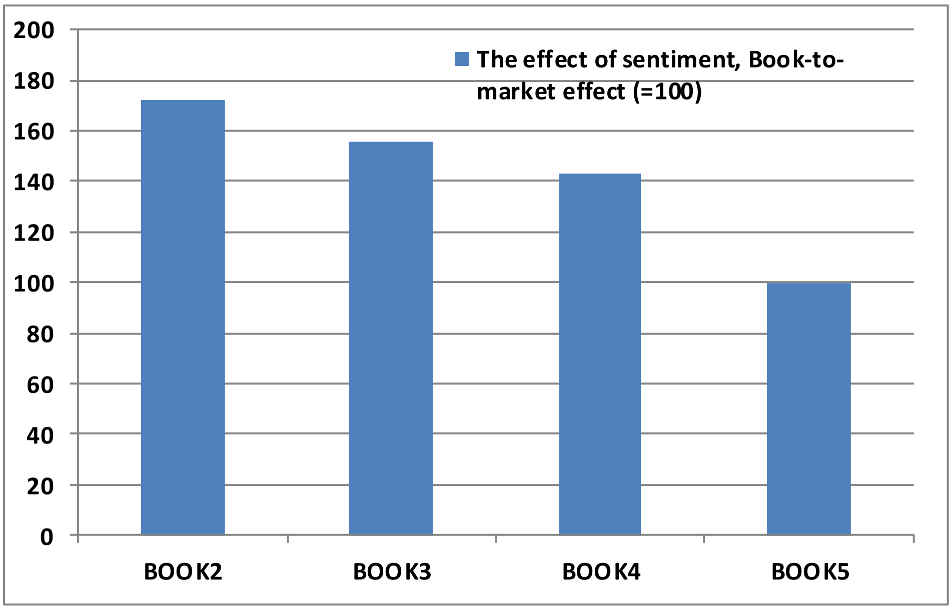

Figure A.4 : The impact of investor sentiment - AAII proxy – Book-to-market effect.

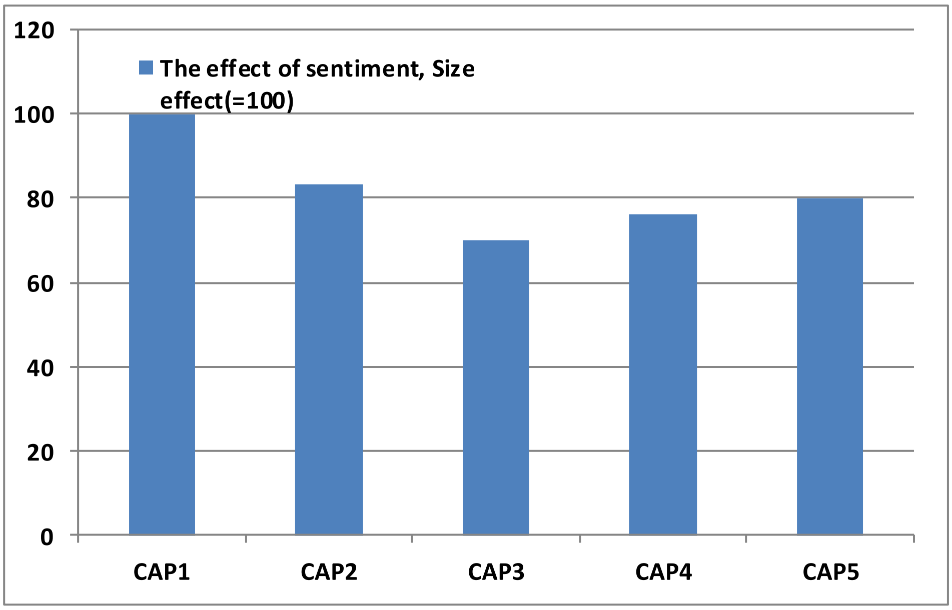

Figure A.5 : The impact of investor sentiment – Baker & Wurgler proxy – Size effect.

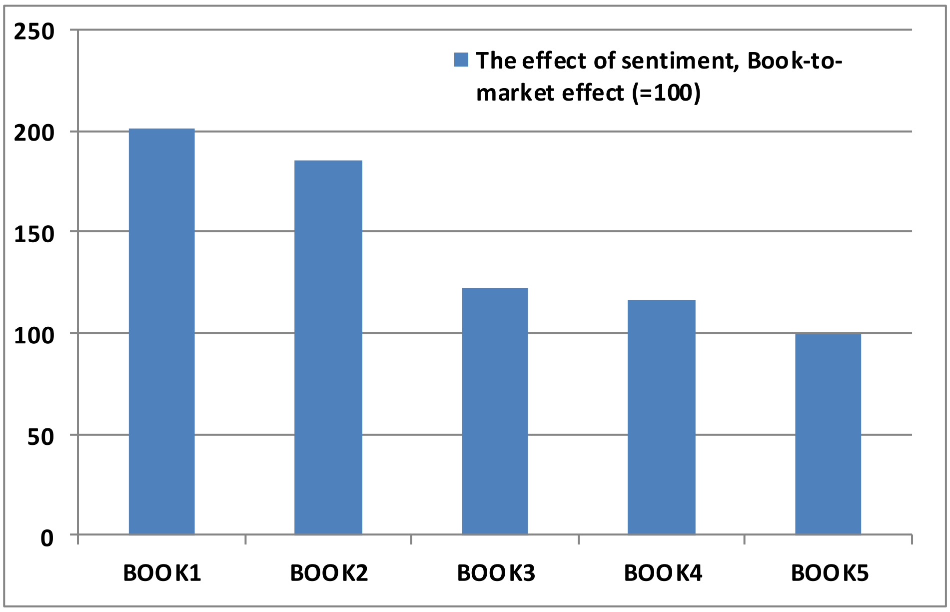

Figure A.6 : The impact of investor sentiment – Baker & Wurgler proxy – Book-to-market effect.

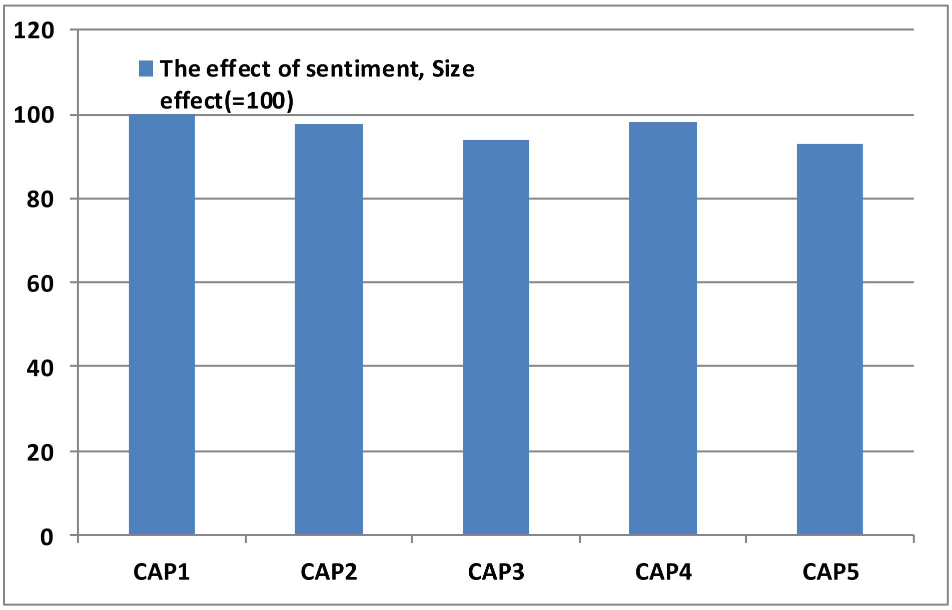

Figure A.7 : The impact of investor sentiment – Put/Call proxy – Size effect.

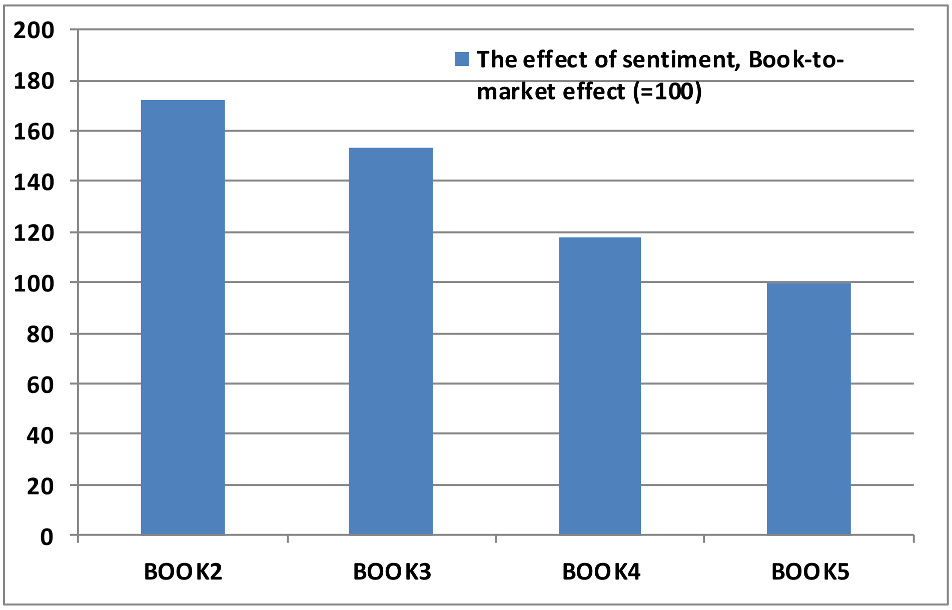

Figure A.8 : The impact of investor sentiment – Put/Call proxy – Book-to-market effect.

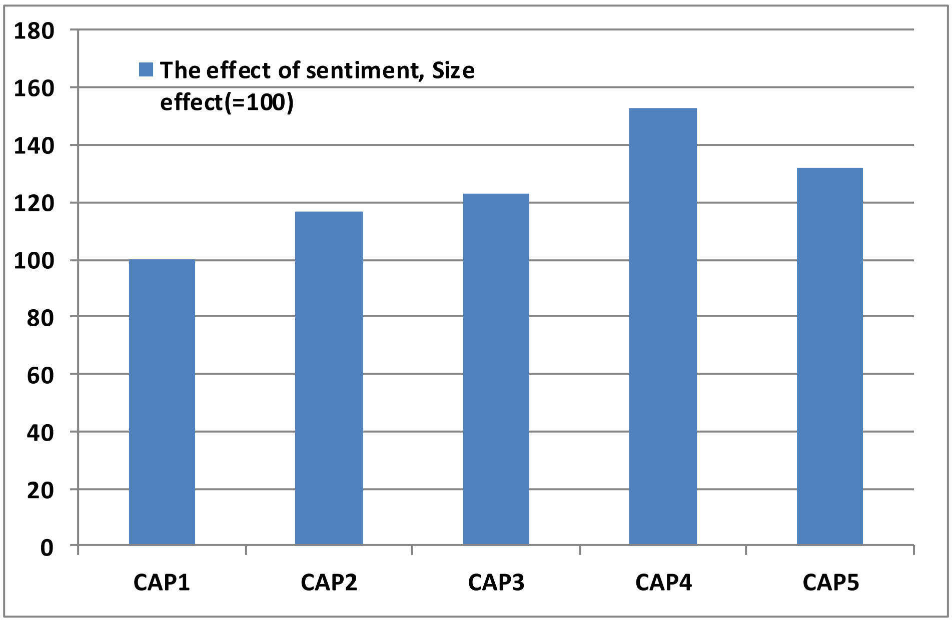

Figure A.9 : The impact of investor sentiment – VIX proxy – Size effect.

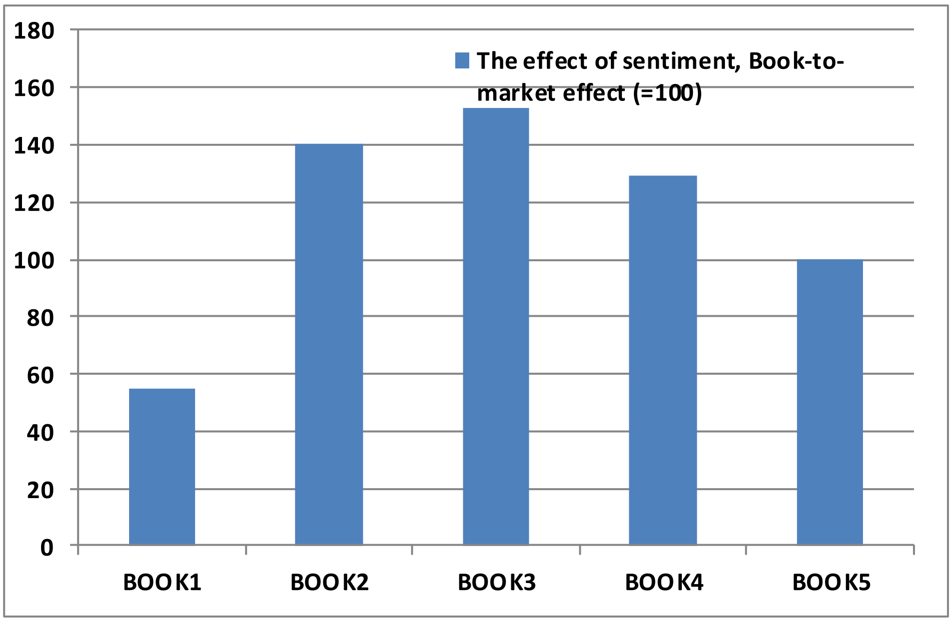

Figure A.10 : The impact of investor sentiment – VIX proxy – Book-to-market.

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- **Uygur U**., and Taş O., 2012: Modeling the effects of investor sentiment and conditional volatility in international stock markets. *İstanbul Finance Congress,* June 13-14, 2012 İstanbul, Turkey.
- **Uygur U**., and Taş O. (2012). Modeling the effects of investor sentiment and conditional volatility in international stock markets. *Journal of Applied Finance and Banking*, *2* (5), 239-260.
- **Uygur U**., and Taş O. (2014). The impacts of investor sentiment on returns and conditional volatility of international stock markets. *Quality and Quantity, 48* (3), 1165-1179.
- **Uygur U**., and Taş O. (2014). The impacts of investor sentiment on different economic sectors: Evidence from Istanbul Stock Exchange. *Borsa İstanbul Review* , *14* (4), 236-241.

OTHER PUBLICATIONS, PRESENTATIONS AND PATENTS:

- **Uygur U**., and Taş O. (2012). Evaluation of the performance of A-Type stock mutual funds in Turkey with parametric and non-parametric methods. *Scottish Journal of Arts, Social Sciences and Scientific Studies*, *2* (1), 86-100.