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Essays on the dynamics of stock returns in emerging markets: Roles of volatility and sentiment in Turkey

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ESSAYS ON THE DYNAMICS OF STOCK RETURNS IN EMERGING MARKETS: ROLES OF VOLATILITY AND SENTIMENT IN TURKEY

A Dissertation

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ABSTRACT

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Emerging stock markets play an important role in portfolio diversification. Accurate depiction of their status is essential for potential investment assessment. This dissertation focuses on two important aspects of emerging markets using Istanbul Stock Exchange ("ISE") as an example: modeling stock return volatility as a measure of risk and exploring potential interaction between stock returns and consumer/business sentiments. ISE is selected as it has no entry restrictions and offers great investment potential with 65% foreign participation.

The first essay focuses on stock return volatility. Potential asymmetric behavior is investigated by looking into how the ISE National-100 Index prices evolve over time and how market participants react to sudden good or bad news. Whether these reactions are priced in the ISE National-100 Index is also confirmed. There are three distinctions from previous studies: (1) Student's t distribution is used in error terms, which is more suitable for non-linear data, (2) Both magnitude and direction of asymmetry is analyzed rather than just direction, and (3) the longer sample period allows more in-depth analysis. The findings suggest that the ISE is inefficient with strong dependencies in stock prices and depicts persistent and asymmetric volatility behavior.

The second essay investigates the bidirectional relationship between consumer/business sentiments and the ISE National-100 Index returns. This is the first study in ISE that treats the sentiment as a joint function of fundamentals-driven and irrationality-driven risk factors and probes the concurrent impact of each component on the ISE National-100 Index returns. It also extends the current literature by incorporating the capital asset pricing model into the calculation of excess returns to validate the findings' robustness. The findings for the second essay support the rational expectations theory that fundamental risk factors have more pronounced and significant effects on stock returns than irrational risk factors. Dissertation's findings imply that the ISE has significant potential for future growth as the number of participants and efficiency increase in the market.

DEDICATION

This dissertation is dedicated to the following people:

To the memory of my grandparents: Sıdıka Günsür, Bekir Günsür, Ramazan Ali Öztürk, and Ayse Öztürk always inspired me in very distinct ways throughout my childhood with their love and teachings. I know that they are watching over me now and are proud of this accomplishment. To my mother: Fatma Öztürk has been the best influence in my life with her persistent confidence, optimism, and endurance. She taught me how to always fight for hope and to never give up when there is failure. Without her endless love and support, I would not have become the person I am today. To my father: Hulusi Öztürk has been the consummate role-model for hard work, honesty and personal sacrifices. He was the one who first encouraged me for graduate school and instilled in me the inspiration to achieve it. I am extremely happy to see what once started as his dream has come to its fruition. To my brother, my sister-in-law and my one and only niece: Gökhan, Ümit and Duru have been the emotional anchors not only during the vagaries of graduate school, but also throughout my entire life. To my love, my soul, my other half, my husband: Ersin Bayram has been proud and supportive. He has shared many uncertainties, challenges and sacrifices during the course of this dissertation. His unconditional love and optimistic attitude have made me a better and more productive person. I cannot express with any words what he means for my being in this world.

Tüm varlığınızla beni ben yaptığınız için hepinize çok teşekkür ediyorum.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION AND BACKGROUND

1.1 Purpose and Contribution of Research

Emerging markets have gained a great deal of importance over the last three decades as they provide great investment opportunities in both the financial and real sectors. There have been a significant number of studies aimed at better understanding how these markets operate and which benefits they have to offer. The early 2000s witnessed the first wave of rising economies in the world: Brazil, Russia, India, and China formed this first group. These first generation emerging markets are referred as the BRIC markets. However, a new group of rising economies have started to take the spotlight in the global economy. This new group includes Vietnam, Indonesia, South Africa, Turkey, and Argentina or VISTA countries (Tseng, 2009).

Emerging stock markets that are located in a developing country as defined by the World Bank's GNP per capita criterion provide further portfolio diversification tools for investors worldwide (Isik et al., 2003). The Istanbul Stock Exchange (ISE) of Turkey meets this criterion and it is classified as an emerging stock market in the literature. Turkey has been a rising and high-growth economy since the ISE started its operations for the first time in 1986. Besides, Turkey is a geopolitically unique country as it straddles in a location where Europe and Asia meet. Moreover, it has one of the leading economies among the VISTA countries due to its relatively higher economic growth rate and large population, which mostly consists of children and young adults (Karatas and Deviren, 2008). In addition, it is a member candidate for the European Union, adding onto its potential for more future growth. It is worth mentioning here that according to the recent predictions made by the United Kingdom Government Trade and Investment Bureau, Turkey's economy will surpass those of Korea, Spain, and Australia by 2050. Thus, this rising emerging market deserves a closer look and examination.

Volatility of stock returns has been an important topic of finance as this type of volatility is affiliated with risk. Modeling of the risk-return tradeoff has been the central task in portfolio theory (Markowitz, 1952, 1959). Stock prices, thus stock returns, may change every day, every hour, and even every minute as new information becomes available to market participants. The general response or attitude of the market participants to new information also affects the overall riskiness of a specific stock exchange. Therefore, it is important to be able to understand how volatility, in other words risk, changes over time in stock markets. Such an issue requires a detailed simultaneous analysis of both, stock returns and changes in stock returns over time. The volatility behavior in emerging stock markets should be studied in depth as the securities in these markets are used for further portfolio diversification purposes by investors worldwide.

Another area of research in finance focuses on the drivers of investor sentiments and if/how these sentiments are related to stock market returns. The relationship between the behavior of investors and stock returns is first discussed by Black (1986). Literature also puts strong emphasis on noise traders, a group of investors who make their trading decisions mostly on noise. Noise is roughly described as inaccurate or false information, which is not sourced from fundamental variables of economics and finance. Literature suggests that noise traders may affect stock prices as a result of their cumulative trading activity. It was hypothesized during the beginning of the 1980s that the effect of noise or noisy trading on stock prices in efficient markets would be both easily wiped away and insignificant, as the market participants would have equal and immediate access to all available, accurate and relevant information. They would bring the stock prices to their intrinsic values efficiently. However, as many of the stock markets were neither semi-strong nor strong form efficient markets, the argument about the effects of noise trading on stock prices have become a controversial topic. Some researchers argue that when the noise traders represent a big portion of market participants, the noisy trading may have a significant effect on stock prices. The actions and decisions of the noise traders are claimed to be more random and unpredictable because they are believed to more prone to exuberance. Studies by De Long et al. (1990, 1991) present a framework for the noise traders' model in stock markets. Many more studies after De Long et al. (1990, 1991) utilize this framework. Subsequent to the noise traders' model, research becomes more specific and focuses on investor sentiment, which drives the actions of noise traders. However, the investigation of the relationship between investor sentiment and stock market returns in emerging markets remains largely unexplored in the literature.

The purpose of this dissertation is to explore the dynamics of the ISE National-100 Index returns from two perspectives: return volatility and consumer/business sentiments. Two essays form the basis of the dissertation: the first one investigates the volatility of the ISE National-100 Index returns as volatility closely relates to the concept of risk for the financial markets. The second essay focuses on the relative simultaneous effects of consumer and business sentiments on the ISE National-100 Index returns and vice versa.

The first essay details how the volatility of the ISE National-100 Index returns has changed between 1988 and 2010. Even though the ISE started its operations officially in 1986, it took a couple of years to establish the stock market and regular trading activities. Therefore, the study sample period starts in 1988 and ends in 2010. There are several contributions of the first essay to the existing literature:

1. It utilizes GARCH type of models which are the most advanced econometrics techniques when it comes to modeling volatility. GARCH models are nonlinear models which enable simultaneous modeling of mean and variance equations of the ISE National-100 Index returns with heteroskedasticity assumption of the variance.
2. Unlike prior studies in the ISE, it assumes a student's t distribution in the error terms for the GARCH models. The student's t distribution assumption is found to be more suitable for financial data as it exhibits high levels of nonlinearity.
3. It investigates asymmetric behavior of the volatility to equal magnitudes of sudden "good" and "bad" news. It accomplishes this by applying a unique GARCH specification that is developed by Glosten, Jagannathan, and Runkle (1994). This special type of GARCH model can be used to analyze asymmetric volatility behavior from two aspects: direction and magnitude. Previous studies that analyze asymmetric volatility behavior in the ISE widely use Exponential GARCH models, (Nelson, 1991), which only make it possible to scrutinize the direction of the asymmetric behavior, not the magnitude.
4. It tests implicitly for weak-form market efficiency by applying the random walk test.

The second essay of this dissertation fills some important gaps in the emerging stock markets literature. It follows the argument that the investor sentiments may contain predictable risk factors besides unexplainable or irrational risk factors in emerging markets. Its contributions to the existing literature can be best summarized as:

1. It shows that consumer and business sentiments can be explained to some extent by some widely used fundamental economic variables in emerging markets.
2. It is one of the pioneer studies investigating the relationships between the stock returns and the consumer/business sentiments in emerging stock markets and it is the first study that

decomposes sentiments into fundamentals driven and irrationality driven components in Turkey and then analyzes the distinct effects of each component on stock returns.

3. It takes into account the potential interaction between consumer and business sentiments by simultaneously incorporating both types of sentiments into the same model when looking at their effects on stock returns.
4. Instead of assuming unidirectional causality between stock returns and sentiments like some other studies, this study looks into the likelihood of bidirectional causality between sentiments and stock returns.
5. As sudden or unanticipated shocks in financial markets may have different implications from anticipated changes, this study focuses on the unanticipated components of sentiments as well as the stock returns. This will help to identify how the market reacts to such shocks as a whole in emerging stock markets. The utilization of the Vector Autoregression models for this purpose is an important contribution to the studies in the ISE.
6. Lastly, when analyzing the impact of sentiments on stock returns, studies usually use continuously compounded returns. This study employs a widely used asset pricing model from the literature. The Capital Asset Pricing Model is used to calculate the excess returns of the ISE National-100 Index. The results from models using both, compounded returns and CAPM fitted excess returns are compared. This is the first study to report such an approach in literature.

Both essays of this dissertation draw essential implications for investors worldwide, firms, governments, creditors, analysts, policy makers, and academic scholars. It will not only help to understand the stock returns, the risk, and the sentiment generating processes in the ISE, but will also improve our general understanding of how emerging stock markets evolve over time in each of these concepts. Chapter II and Chapter III are denoted for the first and second essays, respectively.

1.2 Background and Importance of the Istanbul Stock Exchange

The ISE is the only stock exchange in Turkey. It was formally established in 1985 and started its operations in 1986. The number of companies listed on the ISE increased from 80 at the end of 1986 to 332 at the end of 2010. The market capitalization of the ISE also increased from $13 billion to $336 billion during these 24 years. Kilic (2004) states that Turkey has one of the most liberal foreign regimes in the world, with a fully convertible currency as well as a policy that allows foreign institutional and individual investment in the securities listed on the ISE since 1989. Turkish bonds and stock markets are open to foreign investors, without any restrictions on the repatriation of capital and profits. Foreign investors own at least half of the floating equity in the ISE (Yuksel, 2002). A more recent statistics on the ownership facts in the ISE states that the foreign investors own approximately 67% of the floating equity in this stock market (OECD Facts Sheet, 2010). These facts and evidences further indicate that the ISE is a dynamic emerging stock market, which attracts a great deal of foreign investment. Since its inception in 1986, the ISE has become much larger and it has obtained full membership in globally recognized organizations such as World Federation of Exchanges, Federation of Euro-Asian Stock Exchanges, International Securities Services Association, and many others. The rapid development of the ISE has been attracting more domestic and international investors as a viable portfolio diversification option.

CHAPTER II

MODELING STOCK MARKET VOLATILITY IN TURKEY

2.1 Introduction

Modeling and predicting volatility of stock returns have been intensely debated in finance literature. For the purposes of this dissertation, the word “volatility” simply represents a change in stock index prices over time and it is measured by the standard deviation of the stock index returns. Standard deviation and squared standard deviations, in other words, variance, are two widely used measures of risk, especially in the context of portfolio theory of modern finance (Markowitz, 1952, 1959).Therefore, volatility is an extremely important issue and topic of finance since it represents the levels of risk in stock markets. The major contribution of the modern finance theories is the discovery of the strong relationship between risk and return. The modern portfolio theory suggests (Markowitz, 1952) that there should be a risk-reward tradeoff for each unit of additional risk that risk-averse investors take. The theory highly focuses on reducing the portfolio’s standard deviation by using diversified risk-return securities in one basket. Moreover, in equilibrium, high volatility should correspond to high expected returns (Merton, 1980; Engle et al. 1987). On the other hand, efficient market hypothesis (“EMH”) (Fama, 1970) states that as long as risk is properly priced in the security prices by the agents, markets are efficient. Both hypotheses make two important assumptions of investor characteristics besides other assumptions relating to market characteristics. They assume that the investors are: (1) rational, who always desire to maximize their utility in terms of their wealth, and (2) risk-averse, those who reject a fair gamble, because the decrease in utility caused by the loss is greater than the increase in utility of an equivalent gain. Thus, examining the capability of markets and agents to accurately and timely incorporate any new information is a worthwhile and an extremely essential study to better understand the dynamics of the risk and volatility because rational and risk-averse investors always seek utility maximization without increasing the risk. If the behaviors of risk and return show any predictable patterns, which may be modeled, then arbitrageurs without taking any additional risk may make use of this information and earn consistently higher returns than average returns. This situation obviously violates any form of the EMH and cause financial markets to become riskier as these arbitrageurs may also manage the volatility with their speculations.

It would be prudent here to give a little more explanation about the Efficient Markets Hypothesis before continuing further. The efficient markets hypothesis of finance implies that if new information is revealed, it will be incorporated into the share prices rapidly and rationally, with respect to the direction of the share prices movement and the size of that movement (Fama, 1970). In an efficient market no trader will have an arbitrage opportunity on a share (or other security) that is greater than a fair return for the risk associated with that share (or any other security). The absence of arbitrage possibilities arises because current and past information is immediately reflected in current prices. It is only new information that causes the prices to change. Thus, there are three forms of the market efficiency (Fama, 1970): (1) Weak-form efficiency assumes that all past information is reflected in today's stock price. The random walk test is usually performed to test for the weak form efficiency of markets. (2) Semi-strong form efficiency implies all public information is reflected in a stock's current share price. Thus, neither fundamental nor technical analysis can be used to achieve superior gains. It also suggests that only information that is not publicly available can benefit investors seeking to earn above-average returns on investments. All other information is accounted for in the stock prices and, regardless of the amount of fundamental and technical analysis one performs, above-average returns cannot be achieved. According to the semi-strong form efficiency, half of the market or some fraction of the market is efficient, meaning that the market will be efficient for some securities, not for all securities. Basically, the amount of scrutiny that a security receives is a determinant of how efficient the price is for that specific security. (3) Strong form efficiency implies that profits exceeding average returns cannot be achieved, regardless of the amount of research or information investors have access to. It also states that all information in a market, whether public or private, is accounted for in a stock price. Even insider information could not give an investor the advantage to utilize arbitrage.

Although efficiency and volatility studies on developed countries and their capital markets have been abundant in the finance literature, there is still a big gap in the literature on our knowledge of the stock returns and the volatility drivers in emerging markets. It becomes even more complicated and sophisticated to comprehend the dynamics of the relationship between the stock returns and volatility in emerging markets as these markets already suffer various degrees of market inefficiencies. These markets also give us a chance to study the evolution of stock prices and the patterns of investor behaviors during this evolution. It is vital for individual investors, national and multinational firms, mutual and pension fund managers, and policy makers to be able to understand the risk and the stock return behaviors in these markets as the strength and the direction of their correlations with developed capital markets may vary and they may offer further portfolio diversification opportunities.

One such emerging stock market is the Istanbul Stock Exchange (“ISE”) (Isik et al, 2003). Previous studies on the ISE have focused on testing market efficiency, as introduced by Fama

(1970), and the evolution of the prices of the ISE indices. However, there is little known about the volatility of the returns in the ISE. Odabasi et al. (2004) examine the prices of the ISE in terms of their statistical evolution. The time period used in their study is 1988 to 1999 and they find that expected returns, as approximated by sample means, have not declined and no significant change in volatility is observed during the decade. However, this study does not provide further insight about the level of volatility during the decade; it merely states that there was no change in volatility. Moreover, further studies such as Buguk and Brorsen (2003), Antoniou et al. (1997), and Aktas and Oncu (2006) have all focused on testing the efficiency of the ISE by employing the random walk hypothesis in stock returns (Kendall and Hill, 1953; Malkiel, 1973). Thus, there is a strong need for a study in the ISE that tests for the level of market efficiency while modeling and investigating volatility simultaneously. Modeling of the stock return behavior without the consideration of the risk behavior creates an incomplete picture. My main goal in undertaking this research is to overcome the problem of isolated modeling and to bring new insights and facts to the table that may increase our understanding of emerging stock markets, particularly the Istanbul Stock Exchange.

This essay raises several important research questions and tries to find legitimate and accurate answers to them. First, it asks whether the Istanbul Stock Exchange shows the features of a weak-form efficient market. The random walk test is applied to answer this question. Second, it models the volatility of the ISE National-100 Price Index returns to provide better insights on the risk behavior. The effect of past volatility on current volatility of the ISE National-100 Index returns is also under investigation. Moreover, the asymmetric behavior of the price fluctuations to the same magnitudes of sudden “bad” and “good” news is investigated as this phenomenon is very common in the literature (Nelson, 1991). Volatility studies that focus on the asymmetric behavior puts emphasis on the sudden changes as anticipated changes in volatility may have different implications. Once the volatility of the index returns is modeled, the pricing of the volatility, in other words, risk, is tested to understand the capabilities of the market participants to price aggregate market risk into the security prices.

The contributions of this research to the existing literature are five-fold: (1) It contributes to the literature by modeling volatility and implicitly testing the efficiency of the ISE by focusing on the daily index returns between 1988 and 2010. (2) Literature suggests that the expected future returns can be approximated by calculating the mean for a sample period. This is called "the mean reversion behavior of stock returns" (Poterba and Summers, 1988). Also, the current and the past risk behavior of the securities can be quantified by estimating the variance of the security prices over the same sample period. The GARCH type of models applied in this essay enable simultaneous modeling of the mean and the variance equations for the ISE National-100 Price Index returns. This is a major contribution of the study as there are only handfuls of studies in the ISE that utilize the benefits of such advanced models. (3) Most studies in the ISE, like many others in the literature, assume a normal distribution for the error terms or residuals. In this study, the student's t distribution of the residuals is considered as well as the normal distribution. Some previous studies suggest that the student's t distribution assumption for the error terms is more suitable for financial data (Hansen, 1994; Fernandez and Steel, 1998; Theodossiou, 1998; Branco and Dey, 2001; Bauwens and Laurent, 2005; Jones and Faddy, 2003; Sahu et al., 2003; Azzalini and Capitanio, 2003; Aas and Haff, 2006). To make sure, the distribution of the sample returns are plotted and compared with both, the student's t distribution and the normal distribution. It is displayed that the sample returns exhibit a closer distribution to the student's t distribution. This is one of the first studies that apply the GARCH type of models with two different distribution assumptions in the ISE. (4) Again, related to the econometrics techniques used in this study, nonlinear modeling of ISE National-100 Index returns are achieved. A number of studies provides evidence that it is more suitable for stock returns to be modeled using the nonlinear specifications (Hansen and Singleton, 1982; Scheinkman and Le Baron, 1989; Akgiray, 1989; Rashid and Ahmad, 2008). The linear models assume homoscedastic or constant variance of the error terms. However, plotting the stock price index returns against time reveals a very vital fact that the variance of the stock price index returns over time is generally not constant. This important detail makes the linear models inefficient and insufficient for such data. The application of the nonlinear models for the ISE index returns is very new in the literature and this essay aims to accomplish such application. (5) Finally, the asymmetric response of the stock index prices to the same magnitudes of unanticipated "bad" and "good" news is examined and such asymmetric response is magnified. Moreover, the ability of the market participants to incorporate such asymmetric behavior into the stock prices is questioned. The analysis of such detailed asymmetric behavior for the ISE National-100 Index returns brings one of a kind explanation to the literature.

The implications of the results in this study may serve various parties including national and multinational firms, creditors, investors, analysts, brokers, dealers, regulators and policymakers. There are many factors affecting the expected returns in a stock market. Besides the internal drivers of the stock prices in each listed company, global, economic, political and social determinants also make a huge impact on the stock market as a whole. However, the target in this study is not to analyze or to make comments on the past events that may have had an impact on the ISE National-100 Price Index returns. The attributions of such events and periods are left to the reader for the most part. The firms that consider foreign direct investment to emerging markets may utilize the results as well as the creditors who may partially or fully finance such real sector investments. Individual and institutional investors may incorporate findings in their decision making processes and may make better decisions especially in the context of analyzing the riskiness of the Istanbul Stock Exchange. Regulators and policy makers may observe the shortcomings of the market using the results of this study and may pass regulations or laws to increase the overall efficiency of the stock market. Thus, the implications of the study will be utilized most if this study is seen as a guide that assesses the return and the risk dynamics for the ISE National-100 Index prices from the very early days of the operations in the market.

2.2 Literature Review

This section reviews the relevant literature. It accomplishes that under three main subsections. The first subsection lays evidence for the relationship between the stock returns and the volatility and lists some evidences on the stock return volatility in developed stock markets. The second subsection provides examples for empirical stock return volatility studies in emerging stock markets. Lastly, studies that focus on the efficiency and the volatility of the stock returns in the Istanbul Stock Exchange are conveyed. Possible links between the studies are investigated.

2.2.1 Relationship between Stock Returns and Volatility

The question of whether there is a significant relationship between the stock returns and their volatility has been investigated widely. Existing literature concludes that there is a significant and negative relationship between the stock returns and their volatility (Black, 1976; Poterba and Summers, 1986). However, more emphasis and focus have been put on the efforts in developing econometrics techniques that are sophisticated enough to capture the details and the dynamic properties of the financial time series data used in modeling volatility. In time series data, the average returns thus the volatility changes at every point in time as new observations are added to the sample. Thus, the challenge in modeling such relationship has been about inventing better methodologies to demonstrate more realistic explanations and to provide more accurate forecasts on future return and risk behaviors in the stock markets.

French, Schwert and Staumbaugh (1987) find evidence that the expected market risk premium is positively related to the predictable volatility of stock returns. Their study shows that the unexpected stock market returns are negatively related to the unexpected change in the volatility of stock returns. It is also indirectly implied that there is a positive relationship between expected risk premiums and volatility. On the other hand, some arguments on the weak relationship between mean returns and variance (volatility) have also been proposed and exampled (Ballie and DeGennaro, 1990). Ballie and DeGennaro (1990) suggest that investors consider some other risk measure to be more important than the variance of returns.

The factors affecting stock market volatility are investigated in the literature as well. Some studies in this stream attempt to explain stock market volatility using several macroeconomic variables such as inflation, money supply, interest rates, and industrial production growth (Schwert, 1989a; 1990a). Also, another study concludes that stock market volatility increases after major financial crisis (Schwert, 1989b). The relationship between macroeconomic variables, business cycles, financial crisis and stock return volatility, statistical properties of stock returns, models used to measure volatility, and possible determinants of volatility have been the main theme of research in stock market volatility studies (Schwert and Pagan, 1990; Schwert and Seguin, 1990; Schwert, 1990b, 1990c).

Firm level analysis between the stock prices and the stock market volatility is undertaken and possible explanations at that level are provided. It is documented that individual firms' stock return volatility rises after stock prices fall and this statistical relation is largely due to a positive contemporaneous relation between firm stock returns and firm stock return volatility. Such positive relation is strongest for both small firms and firms with little financial leverage. At the aggregate level, the sign of this contemporaneous relation is reversed. The reasons for the difference between the aggregate- and firm-level relations are also explored (Duffee, 1995).

The optimal sample distribution assumptions for the volatility modeling are also given much attention by some researchers (Andersen et al., 2000 and 1999a). Besides the well-known and widely used methods to measure volatility like Autoregressive Conditional Heteroskedasticity (ARCH) models and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, some other new techniques such as Vector Auto Regression models are used to test robustness of the previous results in the field (Andersen et al. 1999b). However, the GARCH types of models still remain more powerful and stronger models for volatility studies.

Examples of modeling stock return volatility in developed stock markets are plentiful. Though, most of these studies have one important theme in common: they widely utilize the ARCH, GARCH, and Exponential GARCH (EGARCH) models developed by Engle (1982), Bollerslev (1986), and Nelson (1991), respectively or they search for ways to enhance such models to reach better model specifications. Thus, the most important and unique studies in this field are cited and mentioned above.

2.2.2 Return Volatility Studies in Emerging Stock Markets

Stock return volatility studies in particular and volatility in financial markets in general are relatively new in the emerging stock markets literature. However, volatility studies for these markets are rapidly increasing. One of the first studies in modeling stock return volatility for emerging markets focuses on the effects of 1987 Crash. This study investigates such effects for Argentina, Greece, India, Mexico, Thailand and Zimbabwe and finds changes in the ARCH parameter, risk premium and persistence of volatility before and after the 1987 crash. But these noted changes are not uniform and depend upon the individual markets. Factors other than the 1987 crash may also be responsible for the changes (Choudhry, 1996).

A link between foreign direct investment, asset allocation decisions and emerging stock market volatilities is also established in the literature. It is documented that emerging stock market volatilities are different from each other particularly with respect to the timing of capital market reforms. Also, capital market liberalizations often tend to increase correlation between local market returns and the world market but they do not necessarily increase local market volatility (Bekaert and Harvey, 1997).

De Santis and Imrohoroglu (1997) provide one of the most detailed studies in modeling emerging stock market return volatilities and comparing them to developed stock market return volatilities. They state that emerging stock markets exhibit higher conditional volatility and conditional probability of large price changes than mature markets. They find no support for country specific risk premium for emerging stock markets. They detect risk-reward trade off in Latin America, but not in Asia, and no evidence is found for increased price volatility due to market liberalization.

Literature also provides some evidence on when large changes in the volatility of emerging stock markets happen. The types of global and local events that took place during those times are included in the analysis as well. They find that most events that caused large changes in the volatility of the stock returns were local events, except the October 1987 Crash in Far East and Latin American emerging stock markets (Aggarwal et al., 1999).

Examples for such stock return volatility studies in emerging stock markets can be extended very easily. Fazal and Jamshed (1999) provide Pakistani evidence while Siourounis (2002) and Batra (2004) focus on Greek and Indian stock markets, respectively. Selcuk (2005), Michelfelder and Pandya (2005), Chancharat et al. (2007), and Tabak and Guerra (2007) all model volatility of stock returns in Far East and Latin American emerging economies. Mala and Reddy (2007) turn to Fiji stock market as evidence. All of these models use some form of ARCH (Engle, 1982), GARCH (Bollerslev, 1986), and EGARCH (Nelson, 1991) models to better comprehend risk and return behaviors in emerging stock markets.

2.2.3 Return Volatility Studies in the Istanbul Stock Exchange

Studies focusing on the return and volatility behaviors in the Istanbul Stock Exchange are limited. Most studies test for the degree of market efficiency and random walk hypothesis in the Istanbul Stock Exchange (Fama, 1970; Malkiel, 1973). As indicated before, Odabasi et al (2004) examine the prices of the ISE in terms of their statistical evolution using a time period of 1988-1999. They find that expected returns, as approximated by sample means, have not declined and no significant change in volatility is observed during the decade. However, this study does not provide further insight about the level of volatility during the decade; it merely states that there was no change in volatility. More studies such as Buguk and Brorsen (2003), Antoniou et al (1997), and Aktas and Oncu (2006) all test the degree of market efficiency in the ISE by employing the random walk hypothesis to the stock returns. Another important study in the area tests for Overreaction and Underreaction Hypotheses of stock prices as introduced by De Bondt and Thaler in 1985 (Mehdian et al., 2008).

Some recent attempts to analyze the relationship between stock returns and volatility are in place. One of the studies uses ARCH type of models to measure and model volatility in the

ISE. However, ARCH models are usually insufficient to provide accurate results due their inability to incorporate heteroskedastic sample variance (Gokce, 2001). Volatility spillovers from other markets to the ISE is another subject that has attracted few researchers (Berument and Ince, 2005; Darrat and Benkato, 2003). Moreover, effects of some macroeconomic variables and inflation on the volatility of the ISE returns are investigated in depth (Saryal, 2007).

As a result of not having enough number of studies that model stock return volatility, asymmetric behavior of the return volatility, and pricing of such volatilities into the security prices for this particular emerging stock market, it becomes essential to pursue this study and to offer detailed explanations on the volatility issue in the ISE.

2.3 Hypothesis Development

Hypotheses of this essay are developed based on the existing literature mentioned in the previous sections. Efficient markets theory of finance (Fama, 1970) is briefly explained in the Introduction section of this essay. Thus, a brief elaboration on EMH may be useful to the reader to be reminded of the premises of this hypothesis. EMH is one of the most widely used and tested hypothesis of modern finance empirical studies. However, all three forms of EMH are not testable. The weak-form market efficiency is probably the easiest and the most common one to test. The weak-form market efficiency is usually tested by using the random walk model. Whether stock prices follow a random walk is tested by a simple model modification developed by Lo and MacKinlay (1988). Literature uses their methodology extensively as it is simple to apply, yet sophisticated enough to provide accurate results. They hypothesize that the stock prices do not follow a random walk and they are affected by past returns. Following their methodology and results, the first hypothesis of this essay is developed. Lo and MacKinlay state the mathematical expression of the test as:

$$X_t = \mu + X_{t-1} + \delta_t \quad \text{(Eq. 1.1)}$$

where X_t is the logarithm of the stock price at time *t*, μ is an arbitrary drift parameter, and δ_t is the random disturbance term. This specification is very similar to an Auto Regressive model with one term. Thus, this hypothesis is tested by applying the AR (1) process to the sample data during the Box and Jenkins estimation procedure to find the most suitable mean equation specification for the ISE National-100 Index return series in the Methodology section.

H_{1null}: There is no significant relationship between past ISE National-100 Index returns and current ISE National-100 Index returns.

H_1: There is a significant relationship between past ISE National-100 Index returns and current ISE National-100 Index returns.

Previous literature documents many studies that report persistent volatility behavior for stock returns. In fact, it is very common to see such behavior. Thus, hypotheses 2 and 3 are tested to check whether such past volatility effect and persistent volatility also exist in the Istanbul Stock Exchange.

H_{2null}: There is no significant relationship between the past conditional return volatility and the current conditional return volatility in the ISE.

H_2: There is a significant relationship between the past conditional return volatility and the current conditional return volatility in the ISE.

H_{3null}: There is no persistent volatility behavior in the Istanbul Stock Exchange.

H_3: There is persistent volatility behavior in the Istanbul Stock Exchange.

To be in accordance with the EMH, current conditional variance of returns which correspond to current risk should be reflected in the current security prices if the market shows semi-strong form efficiency. In order to test this premise, hypothesis 4 is developed and GARCH in mean models used.

H_{4null}: There is no significant relationship between the current conditional variance (current volatility) of the ISE National-100 Index returns and the current mean (current return) of the ISE National-100 Index returns.

H_4: There is a significant relationship between the current conditional variance (current volatility) of the ISE National-100 Index returns and the current mean (current return) of the ISE National-100 Index returns.

Asymmetric behavior of stock return volatility has been discussed in the literature extensively. A good number of studies find evidence supporting such asymmetric effect. The notion of the idea is that the same magnitudes of unanticipated "bad" and "good" news in the stock markets do not cause same magnitudes of volatility movement. The effects of sudden bad news are more pronounced and greater in magnitudes than the effects of sudden good news (Andersen, Bollerslev, Diebold, and Ebens, 2001). This is also called "*leverage effect*" in the finance literature. Moreover, Overreaction Hypothesis (De Bondt and Thaler, 1985) and Uncertain Information Hypothesis (Brown, Harlow, and Tinic, 1988, 1993) are tested for the Istanbul Stock Exchange and no significant price reversals are reported following favorable news (Mehdian, Nas, and Perry, 2008). This result may indicate some asymmetric behavior in the stock prices of the ISE. Following two hypotheses, hypotheses 5 and 6, aim to test such asymmetric effect and to magnify the difference of volatility changes to the same magnitudes of negative and positive shocks.

H_{5null}: There is no significant difference between the effects of unanticipated positive and negative shocks on the conditional variance of the ISE National-100 Index returns.

H_5 : There is a significant difference between the effects of equal magnitudes of unanticipated positive and negative shocks on the conditional variance of the ISE National-100 Index returns.

H_{6null} : There is no significant relationship between the leverage effect in the conditional variance of the ISE National-100 Index returns and the current ISE National-100 Index prices.

H_6 : There is a significant relationship between the leverage effect in the conditional variance of the ISE National-100 Index returns and the current ISE National-100 Index returns.

Variance of stock returns or volatility is used as a measure of risk in finance. Rational and risk averse investors bear the risk of uncertainty of both future returns and future distributions of returns. Therefore, information obtained from modeling past return and risk behaviors is the only source that can be used in predicting future return and risk behaviors. Testing above hypotheses will give us such detailed analysis of mean (return) and variance (risk) distributions of the ISE National-100 Index prices and will also enable us to make use of forecasts using the models established in this essay.

2.4 Data and Sample

2.4.1 Descriptive Statistics and Unit Root Tests

The data for this study include the daily closings of the ISE National-100 Index prices. The sample period is 12/30/1988 to 01/01/2010 with 5084 observations. The ISE National-100 Index is chosen for the study as this index represents more than 90% of the market capitalization in the ISE. The logarithm of the prices $(\log P_t)$ is shown in Figure 1.1. Usage of the logarithm of the prices is widely accepted in the finance literature as this calculation does not change the second moment of the series and is helpful in the estimation of the daily returns (R_t) of the ISE. The returns are estimated as the logarithmic differences of the index prices. The mathematical expression of the estimation of the return series for the ISE National-100 Index is given by Equation (1.2).

$$R_t = \log(P_t / P_{t-1}) \qquad \text{(Eq.1.2)}$$

FIGURE 1.1
LOGARITHM OF THE ISE NATIONAL-100 INDEX PRICES

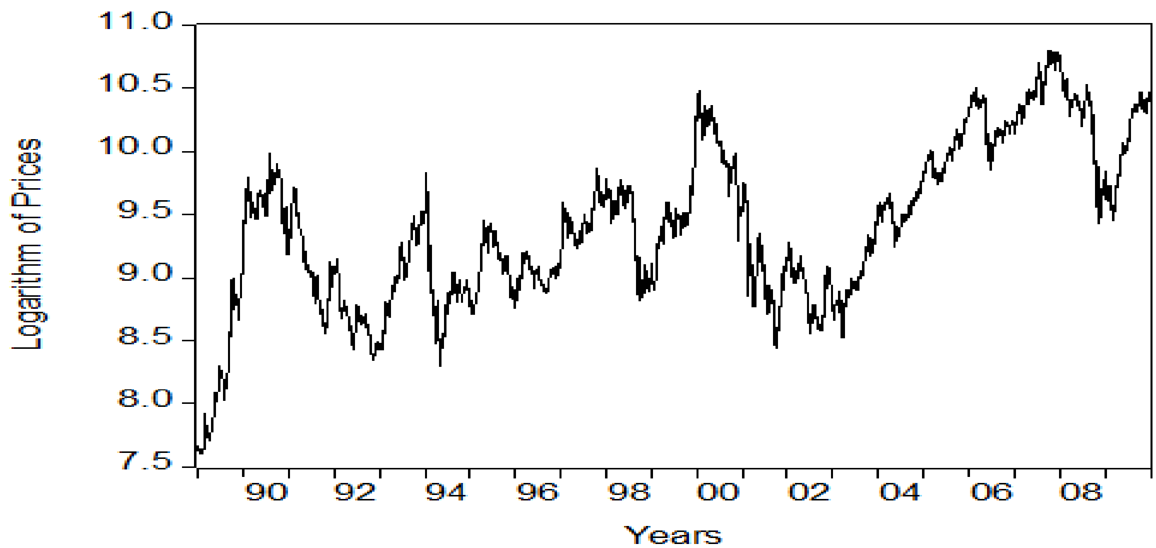


Figure 1.1 exhibits a pattern that shows how the logarithms of daily prices of the ISE change during the time period under investigation. Local minimums can be observed at points in 1994, 1998, 2001, 2003, and 2008. Due to the fact that the volatility is higher when the market goes down, it is important to recognize the events at these dates. The purpose of this study is not to provide a detailed economic, political, social, and global analysis, but rather to model the mean and variance equations that drive ISE National-100 Index prices. Thus, the events will be roughly mentioned, but the implications and comments on such events will be left to readers. During 1991 several important global crisis occurred, including a recession in US economy after the Savings and Loan crisis, Swedish banking crisis, Indian currency crisis, and Russian crisis are some examples that may have had an impact on Turkish economy. The 1994 economic crisis

in Turkey actually started at the end of 1993. It was mostly due to the monetary policy changes in Europe and political instability in the country. The government responded to the economic crisis by launching an IMF backed economic stabilization program on April 5, 1994 (Celasun, 1998; Durgut, 2002).Asian and Russian crisis of 1997 and 1998 respectively affected Turkey in a negative manner. Crisis, which appeared in Thailand in the second half of 1997 and spread to many Asian countries, showed its affect both directly and indirectly. The import and export numbers of Turkey drastically changed during these years due to its reduced comparative advantage caused by the devaluation in Asian economies. Moreover, Asian crisis led foreign investors to quit stock markets and that was the effect of Asian crisis on Turkey finance markets (Yardimcioglu and Genc, 2009).During the last decade though, the ISE National-100 index prices experience their lowest price level in the third quarter of 2001, which corresponds to September 11, 2001 terrorist attacks to the U.S. Then, the market starts recovering but some high volatility is experienced until the end of the first quarter of 2003. March 1, 2003 was a very important date for Turkey because a highly controversial bill that would allow the deployment of U.S Troops in Turkey was being voted on in the Turkish parliament. This bill was rejected in the parliament, causing the Turkish Stock Market prices to drop significantly as the rejection came out as a surprise and affected Turkey's relationships with U.S (Aktas and Oncu, 2006). After the first quarter of 2003, the ISE shows price movements that rise continuously until the end of 2007. This upward movement may be due to the lower inflation rate and stabilized political environment with no coalition. Thus, it may have enhanced investors' beliefs in the market positively. Finally, another local minimum is observed in 2008, which corresponds to the 2008 Financial Meltdown in the U.S during the fall of 2008. The linkage from this crisis is easily seen in the graph.

In order to make sure that stationarity is achieved in the return series, which are financial time series data, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are performed to identify whether the logarithm of price $(\log P_t)$ and the return (R_t) series have any unit roots. According to Dickey and Fuller, the hypothesis of a unit root is tested by estimating the model:

$$\Delta y_t = \alpha_0 + \psi y_{t-1} + \sum_{i=2}^{p} \tau_i \Delta y_{t-i+1} + \varepsilon_t \qquad \text{(Eq. 1.3)}$$

If $\psi = 0$, then the equation is entirely in first differences and has a unit root. To further investigate the unit roots in both series, Phillips-Perron test is also applied to the series. The Phillips-Perron test implies the estimation of the model:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 (t - T/2) + \mu_t \qquad \text{(Eq. 1.4)}$$

Where T is the number of observations and the disturbance term is such that E(μ_t)=0 and tests the null hypothesis of $\alpha_1 = 1$. If $\alpha_1 = 1$, then a unit root is present in the series. Table 1.1 provides some descriptive statistics and the results of the unit root tests for all series ($P_t, \log P_t$ and R_t). The ADF and PP results indicate that the price series (P_t) and the logarithm of price $(\log P_t)$ series have unit roots by failing to reject the null of a unit root presence at the 5 % level. However, the two tests reject the same null hypothesis for the return series (R_t) at the 1% level, concluding that the return series has no unit roots and the data for the return series is stationary.

Figure 1.2 shows the daily returns of the ISE National-100 Index between the years of 1988 and 2010. It can be seen from the figure that the variance of the return series during the time period is not constant over time, which signals the presence of heteroskedasticity. Thus, heteroskedasticity must be taken into account when modeling the volatility of the return series.

TABLE 1.1

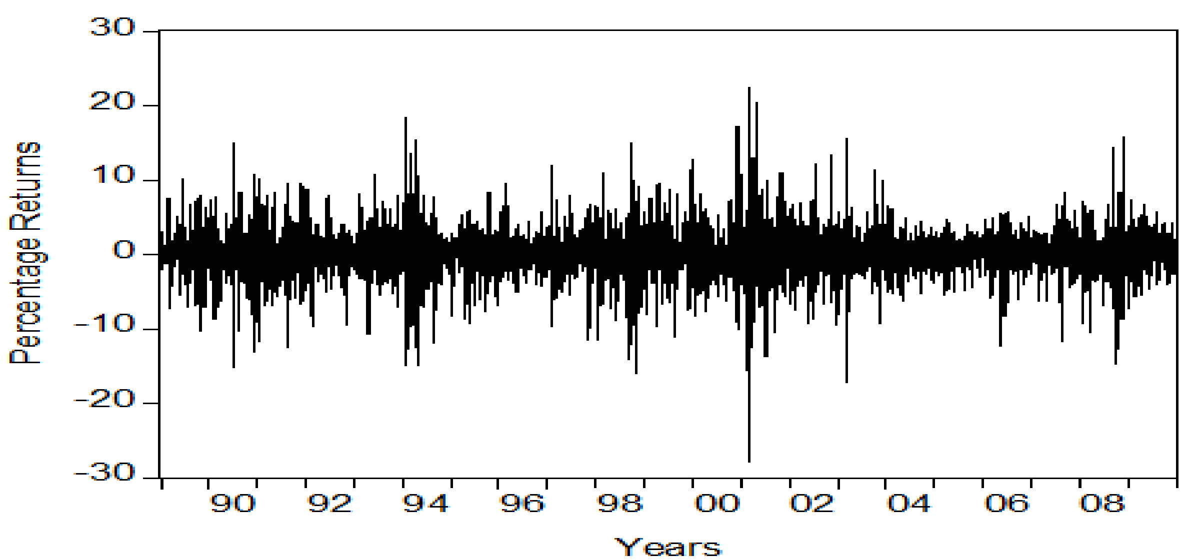
DESCRIPTIVE STATISTICS FOR P_t , $LogP_t$ and R_t SERIES

Statistics	P_t	$LogP_t$	R_t
Observations	5480	5480	5480
Sample Mean	14817.42	9.41	5.18E-04
Variance	9.36E+07	0.40	1.06E-03
Skewness	1.21	-2.10E-03	-1.97E-01
Kurtosis	3.82	2.66	8.00
Unit root test statistics			
Dickey-Fuller (ADF)	-1.73	2.67	-67.81***
Phillips-Perron (PP)	-1.65	-2.64	-67.81***

***, ** Denotes significance at the 1% and 5% levels, respectively. The sample period is from December 30, 1988 to January 1, 2010 for a total of 5480 observations.

FIGURE 1.2

DAILY RETURNS OF THE ISE NATIONAL-100 INDEX PRICES



2.5 Econometric Methodology and Models

2.5.1 Mean Equation of the ISE National-100 Index Returns and ARMA models

In order to model the volatility of the ISE National -100 Index returns, first the mean equation of the return series needs to be modeled using Auto-Regressive Moving Averages (ARMA) models specifications (Enders, 1995). The correct specification of the mean equation model carries a great deal of importance as the residuals obtained from this equation will be used to model the variance equation (volatility) of the return series. Therefore, Box and Jenkins estimation method is used to find the most suitable mean equation specification for the return series of ISE National-100 Index (Box and Jenkins, 1970). Table 1.2 exhibits the results for possible mean equation combinations for the ISE National-100 Index return series. Thus, all possible autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) model combinations have been applied to the data. Akaike Information Criteria (AIC) and Schwarz Bayesian Criteria (SBC) are used to assess the models' fits as they account for additional parameters included in a model.

Autocorrelations function (ACF) and partial autocorrelations function (PACF) for the ISE National-100 Index return series are checked as well. Figure 1.3 shows the ACF and PACF graphs of the daily returns of the ISE National-100 index. The patterns of the return series in these graphs indicate that there are some time dependencies in the return series. Based on AIC, SBC and autocorrelations criteria, MA (1) model is chosen to model the mean equation of the returns because it has the lowest AIC and SBC values, indicating a better model fit.

The MA (1) model for the returns of the ISE is:

$$R_t = a\varepsilon_{t-1} + \varepsilon_t \qquad \text{(Eq. 1.5)}$$

$$\varepsilon_t = R_t - a\varepsilon_{t-1} \qquad \text{(Eq. 1.6)}$$

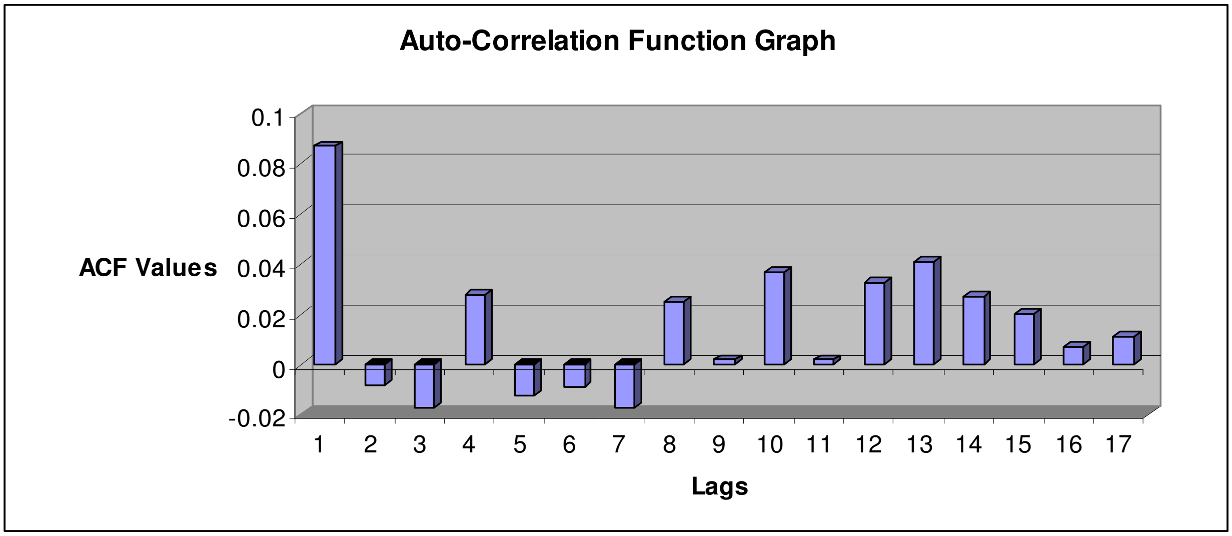
where R_t is the return of the ISE National-100 Index at time t, ε_{t-1} is the residual or error term at time t-1, and ε_t is the residual or error term at time t. "a" is the parameter to be estimated. Thus, the regression in equation 1.5 is run and the residuals (ε_t^*) from this regression are obtained. The sample variance is given by:

$$\sigma^2 = \sum_{t=1}^{T} \varepsilon_t^{*2} / T \qquad \text{(Eq. 1.7)}$$

where T is the number of observations. Then the sample autocorrelations (ACF) and partial autocorrelations (PACF) are estimated for the standardized residuals and the squared standardized residuals. The Ljung-Box Q statistics are calculated for both residual series (standardized and squared standardized residual series). We use 16 lags for the Ljung-Box Q statistics as the optimal lag length for the autocorrelations and partial autocorrelations is approximately 17. Table 1.3 exhibits descriptive statistics and the Ljung-Box Q test statistics for the standardized and squared standardized residuals of the Moving Averages (MA) model with one lag (Ljung and Box, 1978). The result of Ljung-Box Q statistics shows some significant serial correlations for the standardized residual series. Also, we observe significant serial correlations for the squared standardized residuals at 1 % level as well. As a result of these serial auto-correlations, we reject the null of no ARCH or GARCH errors in all lags. Additionally, we perform the Lagrange Multiplier (LM) test for the residuals and it provides the same result of serial correlation in the squared standardized residuals. Thus, we have to take into account that the error terms are time dependent.

FIGURE 1.3

ACF AND PACF GRAPHS OF THE ISE NATIONAL-100 INDEX PRICES



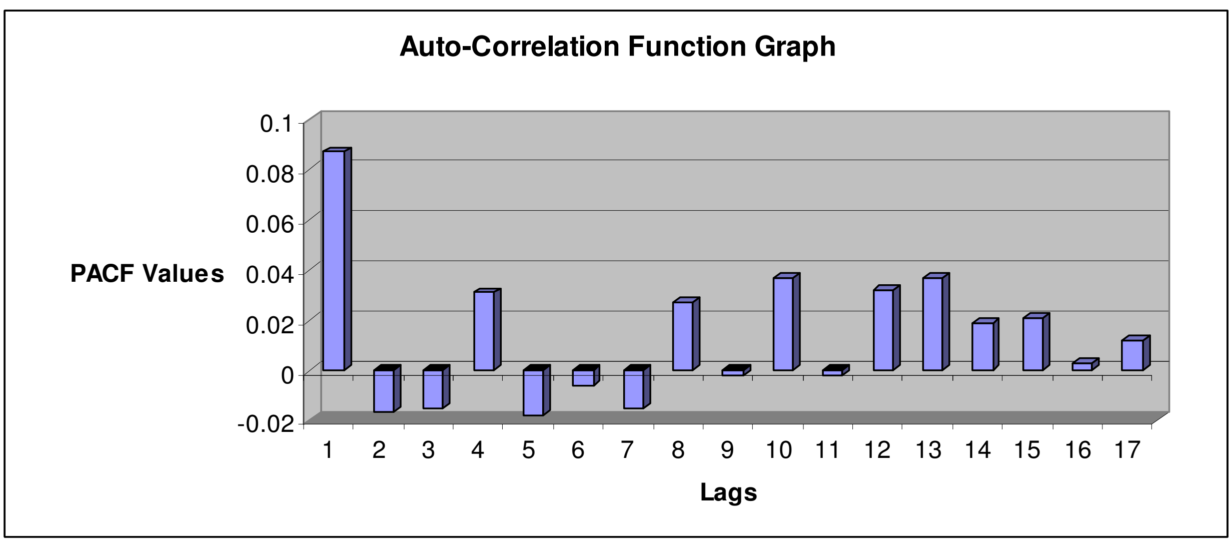


TABLE 1.2

BOX-JENKINS ESTIMATION RESULTS FOR THE MEAN EQUATION OF R_t SERIES

Model	Variable	Coefficient	Std. Error	t-stat	p value	Goodness-of-Fit	
MA (1)	ε_{t-1}	0.09	0.01	6.62	0.00***	AIC	-4.0232
						SBC	-4.0220
MA (2)	ε_{t-1}	0.09	0.01	6.55	0.00***	AIC	-4.0229
	ε_{t-2}	0.00	0.01	-0.30	0.765	SBC	-4.0205
AR (1)	R_{t-1}	0.09	0.01	6.50	0.00***	AIC	-4.0229
						SBC	-4.0217
AR (2)	R_{t-1}	0.09	0.01	6.57	0.00***	AIC	-4.0228
	R_{t-2}	-0.02	0.01	-1.16	0.247	SBC	-4.0204
ARMA (1,1)	R_{t-1}	-0.03	0.15	-0.20	0.844	AIC	-4.0227
	ε_{t-1}	0.12	0.15	0.79	0.431	SBC	-4.0203
ARMA (1,2)	R_{t-1}	0.44	1.03	0.43	0.667	AIC	-4.0224
	ε_{t-1}	-0.36	1.03	-0.35	0.730	SBC	-4.0188
	ε_{t-2}	-0.05	0.09	-0.53	0.599		
ARMA (2,1)	R_{t-1}	0.22	0.65	0.34	0.731	AIC	-4.0224
	R_{t-2}	-0.03	0.06	-0.50	0.617	SBC	-4.0188
	ε_{t-1}	-0.13	0.65	-0.21	0.836		
ARMA (2,2)	R_{t-1}	-0.63	0.27	-2.30	0.021**	AIC	-4.0231
	R_{t-2}	-0.34	0.12	-2.76	0.01***	SBC	-4.0183
	ε_{t-1}	0.72	0.27	2.64	0.01***		
	ε_{t-2}	0.39	0.12	3.22	0.00***		

Notes: ***, ** Denotes significance at the 1% and 5% level respectively. The sample period is December 30, 1988 to January 1, 2010 for a total of 5084 observations. The estimated models for the mean are: (1) $R_t = a\varepsilon_{t-1} + \varepsilon_t$, (2) $R_t = a\varepsilon_{t-1} + b\varepsilon_{t-2} + \varepsilon_t$, (3) $R_t = aR_{t-1} + \varepsilon_t$,(4) $R_t = aR_{t-1} + bR_{t-2} + \varepsilon_t$, (5) $R_t = aR_{t-1} + b\varepsilon_{t-1} + \varepsilon_t$, (6) $R_t = aR_{t-1} + b\varepsilon_{t-1} + c\varepsilon_{t-2} + \varepsilon_t$, (7) $R_t = aR_{t-1} + bR_{t-2} + c\varepsilon_{t-1} + \varepsilon_t$, (8) . AIC and SBC are used to select the best model. The AIC and SBC criteria used because they account for additional parameters included in a model.

TABLE 1.3

DIAGNOSTICS OF THE RESIDUALS FOR MA (1) MODEL

Statistics	Residuals	Squared Residuals
Mean	0.0005	0.0010
Variance	0.0010	7.53E-06
Skewness	-0.15	9.112123
Kurtosis	7.81	141.0737
Ljung-Box Q Statistics		
LB(4)	7.5217	1150.2***
LB(8)	14.860	1436.8***
LB(12)	27.527***	1651.1***
LB(16)	39.214***	1791.9***

***, **, * Denotes significance at the 1%, 5%, and 10% levels. The sample period is December 30, 1988 to January 1, 2010 for a total of 5084 observations. The LB (n) is the nth lag Ljung Box Q test statistic for serial correlation.

2.5.2 GARCH models

As it is mentioned in the previous sections, the possibility of heteroskedasticity should be strongly considered when modeling volatility in stock markets. Odabasi et al (2004) find significant evidence that the variance of the returns of the ISE is not constant. This finding implies that the variance of the model specified for the ISE returns are time dependent and it can be expressed as a function of past realizations, past innovations, and past conditional variances. Bollerslev (1986) extended the work of Engle (1982), who developed the Auto Regressive Conditional Heteroskedasticity (ARCH) model, and introduced the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. GARCH models are found to be extremely useful in Economics and Finance because they are very flexible in modeling second moments. The key insight that ARCH models offer lies in the distinction made between the conditional and unconditional second order moments. Linear ARCH (q) models allow the conditional variance to change over time as a linear function of past errors, while leaving the unconditional variance constant. However, the GARCH (p, q) models allow for both a longer memory and a more flexible lag structure that assume heteroskedastic conditional and unconditional variances.

Besides a GARCH (1, 1) model, a GARCH in mean (GARCH-M), an exponential GARCH (EGARCH), an exponential GARCH in mean (EGARCH-M), a Glosten-Jagannathan-Runkle GARCH (GJR-GARCH), and a Glosten-Jagannathan-Runkle GARCH in mean (GJR-GARCH-M) models are applied to the data. Specifications and explanations for each model are briefly given in the next sections.

Another important issue is the distribution of the error terms. Normal distribution assumption can be used but close examination of the distribution of the ISE National-100 index returns reveals that applying student's t error distribution in GARCH modeling is more suitable (Bollerslev, 1987; Tellez et al., 2009)[1]. Several studies show that returns are fat-tail distributed (Bachelier, 1900; Mandelbrot, 1963; Fama, 1965). Moreover, excess of kurtosis like in this case indicates a non-normal distribution. Thus, the results of GARCH models both under normal distribution and student's t distribution assumptions are reported for comparison and robustness checks. However, GARCH models with the student's t distribution in the error terms consistently provide better model fits. As a result, all of the implications and comments of the study are based on the GARCH models with student's t distribution assumption.

GARCH Model

Effective modeling of stock returns and volatility of the stock returns require accurate representation of variance. However, it was a challenge to come up with as basic versions of least squares models assume that the expected value of all error terms, when squared, is the same at any point. Such assumption is called homoscedasticity and it is the central focus of the

[1] See the figure in Appendix A.1 for the distribution of the ISE National-100 Index Returns. This figure compares the distribution of the returns against the normal distribution and the student's t distribution. It lays evidence that the student's t assumption for the daily returns of the ISE National-100 Index is more suitable than the normal distribution assumption.

ARCH/GARCH models. When the variances of the error terms are not equal as it is for most financial data, the term “heteroskedasticity” defines the non-constant behavior of the variance.

Previous studies before Engle (1982) considered many specifications to model the mean equation of financial returns and these specifications had been used to forecast future financial returns. Thus, there were no methods available to model the variance of such returns and to measure its effect on current returns. The need and motivation for the ARCH/GARCH models came from this gap in econometrics. Earlier attempts in the field assumed that the variance of tomorrow’s return was an equally weighted average of the squared residuals from the all prior days of tomorrow. However, the equal weight assumption of the squared residuals did not seem like a well fit assumption as more recent events may be more relevant and it may be more logical to assign them with higher weights. Thus, the Auto Regressive Conditional Heteroskedasticity (ARCH) model developed by Engle (1982) corrects for this problem by letting these weights to be parameters to be estimated in the model. The ARCH model allows the data to determine the best weights to use in forecasting the variance.

Bollerslev (1986) extends the ARCH model and created a useful generalization, simply named “Generalized Auto Regressive Conditional Heteroskedasticity” (GARCH) model. This model also assumes a weighted average of past squared residuals but it puts declining weights that never go completely to zero. The GARCH model is a more parsimonious and easy-to-estimate model that has stronger prediction power when modeling conditional variances. The GARCH model with its mostly used specification state that the best forecaster of the tomorrow’s variance is the weighted average of the long-run average variance, the variance predicted for today, and today’s new information that is captured by today’s squared residual (Engle, 2001).

Equation 1.8 is a mathematical expression of the Moving Average model with one term which is detected as the most suitable mean equation for the ISE National-100 Index returns. Thus, the mathematical derivations and expressions of the GARCH model, which models both mean and variance equations of the ISE National-100 Index returns simultaneously, are presented below:

$$R_t = a\varepsilon_{t-1} + \varepsilon_t \qquad \text{(Eq. 1.8)}$$

If the error term process is:

$$\varepsilon_t = v_t\sqrt{h_t} \text{ where } \sigma_v^2 = 1, E(v_t) = 0 \text{ and}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2 + \sum_{i=1}^{p}h_{t-i} \qquad \text{(Eq. 1.9)}$$

Then the sequence { v_t } is a white noise process and the conditional and unconditional means of ε_t are equal to zero. The GARCH (p, q) model is given by equations 1.10 and 1.11.If ε_t depends on past realizations and past conditional variances, then it is given by (Enders, 1995):

$$\varepsilon_t = v_t(\alpha_0 + \sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2 + \sum_{i=1}^{p}\beta_i h_{t-i}) \qquad \text{(Eq. 1.10)}$$

where v_t is a white noise process with zero mean and constant variance. Therefore, the conditional variance of ε_t is:

$$h_t = \alpha_0 + \sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2 + \sum_{i=1}^{p}\beta_i h_{t-i} \qquad \text{(Eq. 1.11)}$$

Maximum Likelihood Estimation (MLE) technique gives estimates for the parameters in the above equation in one step process by using a search algorithm. Using AIC and SBC criteria for the model fit, p=1 and q=1 specification are found to be optimal in modeling conditional variance of the ISE National-100 index returns. The statistical significance of the coefficients of the conditional variance equation gives us information about the determinants of current volatility. By close examination of these coefficients, it can be specified how much of the current volatility depends on past realizations and how much of it depends on past volatility.

GARCH-M Model

In GARCH-M model, the conditional variance of the current return (h_t) is added in the right hand side of equation 1.12, which is the mean equation for the returns. This model is presented by Engle, Lilien and Robins in 1987. This new term is introduced into the mean equation of the returns in order to identify whether the current conditional variance, volatility of the series, which is a function of past realizations, past innovations, and past conditional variances has any impact on the current returns. The mathematical expression of the GARCH-M (1, 1) model is:

$$R_t = a\varepsilon_{t-1} + \phi h_t + \varepsilon_t \qquad \text{(Eq. 1.12)}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + u_t \qquad \text{(Eq. 1.13)}$$

If ϕ is statistically significant, then the current volatility of the returns is priced in the current index prices, meaning that the market is accounting for the volatility changes in current asset prices.

EGARCH Model

The GARCH models ignore information on the direction of returns and only account for the magnitudes. However, it is very convincing that the direction may also affect volatility of the returns. In order to bring more explanation to this phenomenon, the exponential GARCH (EGARCH) model is developed by Nelson in 1991. The main purpose of EGARCH models is to test for the asymmetrical response of the market to the same magnitudes of positive and negative shocks. The model expression for an EGARCH (1, 1) model is:

$$R_t = a\varepsilon_{t-1} + \varepsilon_t \quad \text{(Eq. 1.14)}$$

$$\log h_t = \alpha_0 + \alpha_1(\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}) + \mu(\left|\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}\right| - \eta) + \beta_1 \log h_{t-1} + u_t \quad \text{(Eq. 1.15)}$$

The coefficients, α_1 and μ, are asymmetry coefficients and the possible statistical significances of these coefficients in the model imply that the current volatility is asymmetrically affected by the same magnitudes of negative and positive shocks in the market.

EGARCH-M Model

The EGARCH-M model like the EGARCH model linked the asymmetric conditional variance between market risk and expected return (Nelson, 1991).As it is in the GARCH-M model, this model also adds the conditional variance of the current returns (h_t) to the right hand side of the mean equation for the index returns. The mathematical expression of the EGARCH-M model follows as:

$$R_t = a\varepsilon_{t-1} + \phi \log h_t + \varepsilon_t \quad \text{(Eq. 1.16)}$$

$$\log h_t = \alpha_0 + \alpha_1(\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}) + \mu(\left|\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}\right| - \eta) + \beta_1 \log h_{t-1} + u_t \quad \text{(Eq. 1.17)}$$

Moreover, if ϕ is statistically significant in the mean equation, it indicates that a strong relationship between the asymmetric behavior of current volatility and the current index returns exist.

GJR-GARCH Model

Glosten, Jagannathan, and Runkle (1994) show how to allow the effects of good and bad news to have different effects on volatility. The tendency for volatility to decline when returns rise and to rise when returns fall is often called the leverage affect. (Enders, 1995) According to Glosten, Jagannathan, and Runkle, the leverage effect can be measured by applying $\varepsilon_{t-1} = 0$ as a threshold such that shocks greater than the threshold have different effects than shocks below the threshold. The threshold GARCH (GJR-GARCH) process we use in this study is:

$$R_t = a\varepsilon_{t-1} + \varepsilon_t \quad \text{(Eq. 1.18)}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \lambda D_{t-1}\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + u_t \quad \text{(Eq. 1.19)}$$

Where D_{t-1} is a dummy variable that is equal to 1 if $\varepsilon_{t-1} < 0$ and is equal to zero if $\varepsilon_{t-1} \geq 0$. If the coefficient λ is statistically significant, it can be concluded that negative shocks have different effects on the current volatility than positive shocks and the magnitude of this effect can be identified from the size of the coefficient.

GJR-GARCH-M Model

GJR-GARCH in mean model carries the current conditional variance to the mean equation to identify whether such magnitudes of asymmetric behavior of current conditional variance has a significant impact on the mean of the sample. It has a mean equation extension that is the only difference from the previously explained GJR-GARCH model. Equations 1.20 and 1.21 represent the mathematical expression of this model.

$$R_t = a\varepsilon_{t-1} + \phi h_t + \varepsilon_t \quad \text{(Eq. 1.20)}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \lambda D_{t-1}\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + u_t \quad \text{(Eq. 1.21)}$$

2.6 Results

The results of the study are reported in three main subsections. The first subsection focuses only on the results for the full sample period. The second section highlights the findings for the subsample periods of 12/30/1988-12/30/1998 and 12/31/1998-01/01/2010. The last subsection compares and contrasts results across all sample periods while identifying the final status of the hypotheses developed. The implications of each result are made right on point when the results are revealed as well as the last subsection that provides important remarks of the implications.

2.6.1 Full Sample GARCH Results

Tables1.4 and 1.5 report the results of Maximum Likelihood estimation (MLE) for variously specified types of GARCH models applied in this study. As indicated before, the comments of the results are based on Table 1.5 due to better model fits under the student's t distribution assumption of the error terms.

The random walk model is tested while searching for the best fitted mean equation for the ISE National-100 Index returns. The AR (1) model in Table 1.2 has the same model specification with the model that tests the Random Walk Hypothesis. The coefficient for the variable "R_{t-1}" is significant at the 1% level. This indicates that the first null hypothesis is rejected for the ISE National-100 Index returns that there is a significant relationship between the past and current returns of the ISE National-100 Index. Current returns of the ISE National-100 Index is being explained and predicted by the past returns to some extent and the stock returns are not produced by a random process. Thus, a portion of future returns can be predicted by using past returns information and this result also rejects the weak-form efficiency for the ISE National-100 Index (Fama, 1970).

The results for the GARCH (1, 1) model for the ISE National-100 Index return series show that all of the coefficients are significant at the 1% level. The second null hypothesis, which states no significant relationship between the current conditional variance and the past conditional variance, is rejected. The coefficient for the lagged conditional variance, β_1, indicates that 82% of past volatility in the ISE National-100 Index returns is carried over into the next period. The graph of the conditional standard deviation estimated by GARCH (1, 1) model can be found in Appendix A.2[2]. The pattern of the conditional standard deviation graph matches with the pattern of the volatility that R_t sequence experiences (Figure1. 2). Moreover, the results for the GARCH (1, 1) model reveal that the sum of the ARCH and the GARCH coefficients in the conditional variance equation, α_1 and β_1, is smaller than one, and such outcome indicates that the conditional variance has exhibited long persistence of volatility (Bollerslev, 1986). Thus, the third null hypothesis is rejected and strong persistence of the past volatility in the ISE is observed for the full simple period.

In order to determine whether the conditional variance (volatility) has any significant impact on the current returns or index prices, the GARCH-M (1, 1) model is employed. The coefficient "ϕ", which symbolizes the conditional variance of the returns in the mean equation is significant at the 1% level. This indicates that the current conditional variance (current volatility) of the ISE National-100 Index returns has a significant impact on the current mean (current return) of the ISE National-100 Index returns, resulting in the rejection of the fourth null hypothesis for the essay. The implication of such result could be attributed to both that the market perceives volatility change and therefore it adjusts its prices based on the current volatility and, that the market is capable of incorporating this information in the asset prices.

There have been few studies on the ISE that considers the mean of the returns also being affected by asymmetric volatility (Aybar and Yavan, 1998; Selcuk, 2005). Thus, EGARCH (1, 1) and EGARCH-M (1, 1) models introduced by Nelson (1991) are applied. These models have the ability to show both whether there are any significant asymmetries in the conditional variance equation of the returns as well as whether the current returns are significantly affected by

[2] The graphs of the conditional standard deviations for the GARCH-M (1, 1), EGARCH (1, 1), EGARCH-M (1, 1), GJRGARCH (1, 1), and GJRGARCH-M (1, 1) models can be viewed in Appendices A.3, A.4, A.5, A.6, A.7, respectively.

possible asymmetric behavior of the current conditional variance. The results show that asymmetry coefficients "β_1" and "μ" are both significant at the 1 % level and there exists a significant asymmetric behavior in the conditional variance of the ISE National-100 Index returns to the same magnitudes of unanticipated positive and negative shocks. Moreover, the conditional variance coefficient in the mean equation, ϕ , is also significant at the 1% level, indicating that the asymmetric conditional variance has a significant impact on current returns. Such results provide support for the rejection of the fifth null hypothesis.

To further investigate the asymmetry issue, a binary dummy variable that takes on the value of one if $\varepsilon_{t-1} < 0$ and takes on the value of zero if $\varepsilon_{t-1} \geq 0$ is created (Glosten, Jagannathan, and Runkle, 1994). The coefficient for this dummy variable, λ, is significant at the 1% level in the conditional variance equation. Therefore, the change in conditional variance caused by unanticipated negative shocks is greater by 0.7 per unit variance change, even when the magnitudes of both unanticipated positive and unanticipated negative shocks are the same. As a consequence, the sixth null hypothesis for this research is rejected. Accordingly, previously mentioned "leverage effect" is seen for the ISE National-100 Index return volatility. One implication of this result in an emerging stock market such as the ISE may be that the market becomes more nervous when negative shocks take place (Siourounis, 2002). Thus, small investors may panic in response to these negative shocks and they may sell their stocks in order to avoid steeper losses. This is a phenomenon also experienced in developed stock markets and called "loss aversion" (Tversky and Kahneman, 1991).The results for the GJRGARCH-M (1,1) display that such leverage effect in the current conditional variance is significantly affecting the current mean of the ISE National-100 Index returns as well. However, the magnitude and the persistence of the shock may vary substantially (Siourounis, 2002).

TABLE 1.4
MLE OF THE GARCH MODELS WITH NORMAL DISTRIBUTION OF THE ERROR TERMS ASSUMPTION-FULL SAMPLE

Coefficient	GARCH (1,1)	GARCH-M (1,1)	EGARCH(1,1)	EGARCH-M (1,1)	GJRGARCH (1,1)	GJRGARCH-M (1,1)
1. a	0.09***	0.09***	0.10***	0.09***	0.13***	0.13***
	(0.014165)	(0.014280)	(0.013610)	(0.013681)	(0.015712)	(0.015529)
2. α_0	3.35E-05***	3.44E-05***	-0.48***	-0.49***	0.000100***	9.94E-05***
	(2.90E-06)	(2.94E-06)	(0.026826)	(0.027460)	(5.27E-06)	(5.26E-06)
3. α_1	0.13***	0.13	-0.03***	-0.03***	0.12***	0.12***
	(0.006170)	(0.006261)	(0.005565)	(0.005728	(0.008007)	(0.007918)
4. β_1	0.85***	0.84***	0.96***	0.96***	0.59***	0.59***
	(0.006741)	(0.006818)	(0.003402)	(0.003465)	(0.013079)	(0.013303)
5. ϕ *(Garch term in the mean eq.)*		1.03		1.03**		-1.05**
		(0.427474)		(0.425100)		(0.485679)
6. μ			0.24***	0.24***		
			(0.007900)	(0.008006)		
7. λ *(Leverage)*					0.36***	0.36***
					(0.033791)	(0.034289)
Goodness-of-fit Measures						
AIC	-4.259339	-4.260020	-4.251736	-4.252188	-4.436566	-4.437035
SBC	-4.254515	-4.253990	-4.245707	-4.244952	-4.430536	-4.429799
Usable observations	5480	5480	5480	5480	5480	5480
Degrees of Freedom	5476	5475	5475	5474	5475	5474

***, ** Denotes significance at the 1% and 5% level, respectively. Standard errors are reported in parentheses. The sample period is December 30, 1988 to January 1, 2010 for a total of 5084 observations. The GARCH (1, 1) model we estimate is: $R_t = a\varepsilon_{t-1} + \varepsilon_t$ where $\varepsilon_t = v_t\sqrt{h_t}$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ .GARCH-M (1, 1) is: $R_t = a\varepsilon_{t-1} + \phi h_t + \varepsilon_t$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ .EGARCH (1, 1) is: $R_t = a\varepsilon_{t-1} + \varepsilon_t$ and $\log h_t = \alpha_0 + \alpha_1(\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}) + \mu(\left|\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}\right| - \eta) + \beta_1 \log h_{t-1}$. "η" is a stable variable. EGARCH-M (1, 1) is: $R_t = a\varepsilon_{t-1} + \phi h_t + \varepsilon_t$ and $\log h_t = \alpha_0 + \alpha_1(\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}) + \mu(\left|\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}\right| - \eta) + \beta_1 \log h_{t-1}$. GJRGARCH (1, 1) is: $R_t = a\varepsilon_{t-1} + \varepsilon_t$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \lambda D_{t-1}\varepsilon_{t-1}^2$ and GJRGARCH-M (1, 1) is: $R_t = a\varepsilon_{t-1} + \phi h_t + \varepsilon_t$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \lambda D_{t-1}\varepsilon_{t-1}^2$.

TABLE 1.5
MLE OF THE GARCH MODELS WITH STUDENT'S T DISTRIBUTION OF THE ERROR TERMS ASSUMPTION-FULL SAMPLE

Coefficient	GARCH (1,1)	GARCH-M (1,1)	EGARCH(1,1)	EGARCH-M (1,1)	GJRGARCH (1,1)	GJRGARCH-M (1,1)
1. a	0.08***	0.08***	0.08***	0.08***	0.12***	0.16***
	(0.014101)	(0.014171)	(0.013884)	(0.013959)	(0.015186)	(0.010278)
2. α_0	3.91E-05***	4.11E-05***	-0.60***	-0.62***	1.35E-04***	2.82E-04***
	(5.90E-06)	(6.07E-06)	(0.057164)	(0.058278)	(1.11E-05)	(2.59E-05)
3. α_1	0.15***	0.16***	-0.05***	-0.05***	0.13***	0.13***
	(0.013701)	(0.013978)	(0.011731)	(0.011823)	(0.016850)	(0.020389)
4. β_1	0.82***	0.81***	0.95***	0.94***	0.44***	0.17***
	(0.013584)	(0.013904)	(0.007190)		(0.026755)	(0.023957)
5. ϕ *(Garch term in the mean eq.)*		1.08***		0.91**		-6.31***
		(0.400013)		(0.398637)		(0.700407)
6. μ			0.30***	0.30***		
			(0.019643)	(0.019756)		
7. λ *(Leverage)*					0.70***	1.46***
					(0.105514)	(0.227578)
Goodness-of-fit Measures						
AIC	-4.319877	-4.320905	-4.319562	-4.320018	-4.488728	-4.535858
SBC	-4.313847	-4.313669	-4.312326	-4.311576	-4.481492	-4.527416
Usable observations	5480	5480	5480	5480	5480	5480
Degrees of Freedom	5476	5475	5475	5474	5475	5474

***, ** Denotes significance at the 1% and 5% level, respectively. Standard errors are reported in parentheses. The sample period is December 30, 1988 to January 1, 2010 for a total of 5084 observations. The GARCH (1, 1) model we estimate is: $R_t = a\varepsilon_{t-1} + \varepsilon_t$ where $\varepsilon_t = v_t\sqrt{h_t}$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ .GARCH-M (1, 1) is: $R_t = a\varepsilon_{t-1} + \phi h_t + \varepsilon_t$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ .EGARCH (1, 1) is: $R_t = a\varepsilon_{t-1} + \varepsilon_t$ and $\log h_t = \alpha_0 + \alpha_1(\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}) + \mu(\left|\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}\right| - \eta) + \beta_1 \log h_{t-1}$. "η" is a stable variable. EGARCH-M (1, 1) is: $R_t = a\varepsilon_{t-1} + \phi h_t + \varepsilon_t$ and $\log h_t = \alpha_0 + \alpha_1(\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}) + \mu(\left|\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}\right| - \eta) + \beta_1 \log h_{t-1}$. GJR-GARCH (1, 1) is: $R_t = a\varepsilon_{t-1} + \varepsilon_t$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \lambda D_{t-1}\varepsilon_{t-1}^2$ and GJRGARCH-M (1, 1) is: $R_t = a\varepsilon_{t-1} + \phi h_t + \varepsilon_t$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \lambda D_{t-1}\varepsilon_{t-1}^2$.

The goodness-of-fit measures across all applied models are compared. The GJRGARCH-M (1, 1) model has a relatively better fit compared to all others by the virtue of having the lowest AIC and SBC values. In order to better assess the fit of the GJRGARCH models, diagnostics checking of the standardized residuals and standardized residuals squared is performed as well. The results for the residual diagnostics analysis is shown in Table 1.6.

TABLE 1.6

DIAGNOSTICS OF THE RESIDUALS FOR GJRGARCH MODELS

Statistics	**GJRGARCH (1,1)**	**GJRGARCH-M (1,1)**
Standardized Residuals		
Mean	0.19	0.44
Variance	0.99	0.86
Skewness	1.22	1.63
Kurtosis	5.51	6.92
Ljung-Box Q Statistics		
LB(4)	6.90	12.37**
LB(8)	11.41	21.07***
LB(12)	19.69*	32.67***
LB(16)	30.70**	49.17***
Stand. Residuals Squared		
Ljung-Box Q Statistics		
LB(4)	1.36	7.56
LB (8)	15.60**	26.27**
LB(12)	25.64**	39.89**
LB(16)	36.27***	59.93***

***, **, *Denote significance at the 1 %, 5% and 10% levels, respectively. The sample period is December 30, 1988 to January 1, 2010 for a total of 5084 observations. The LB (n) is the nth lag Ljung Box Q test statistic for serial correlation.

Correct specification of the model implies that residuals will have a zero mean, constant variance, and no serial correlation. The Ljung-Box Q test for serial correlation does indicate serial correlations for the standardized residuals for both GJRGARCH and GJRGARCH-M models. Further, it does indicate some serial correlation for the standardized residuals squared after the 8th lag for the GJRGARCH (1, 1) model. On the other hand, GJRGARCH-M (1, 1) model shows serial correlations after the 8th lag in the squared standardized residuals as well. However, GJRGARCH (1,1) model reveals a mean for the standardized residuals that is closer to zero and a variance that is closer to unity compared to GJRGARCH-M (1,1) model's standardized residuals. Therefore, GJRGARCH (1, 1) model better explains the dependencies of the first and second moments that are present in the ISE National-100 Index return series. Furthermore, the GJRGARCH-M (1, 1) model raises serious suspicions about a possible nonlinear behavior of the ISE National-100 Index returns that is beyond the explanation of the GARCH type models which are also nonlinear models.

2.6.2 Subsample Periods' GARCH Results

In order to have a better understanding and a further insight about the behavior of the ISE National-100 Index return volatility, the full sample period is divided into two subsample periods. These subsamples are the two decades within the period. Having the subsample periods creates a comparison across different decades as well as giving an opportunity to observe the evolution of the volatility in ISE.

First and second sample periods consist of observations from 12/30/1988 to 12/30/1998 and from 12/31/1998 to 01/01/2010, respectively. As it was performed earlier for the full sample period, the Box-Jenkins estimation method is applied to each subsample period as well to determine the best fit for the mean equations of the ISE National-100 Index returns for subsamples. Tables 1.7 and 1.8 show the results of these estimations for the subsamples. ARMA (2, 2) model specification is the best fit for the mean equation of the ISE National-100 Index returns for the first subsample period whereas ARMA (1, 2) model provides the most suitable specification for the mean equation of the second subsample period. These model specifications are used for the GARCH models in question for their respective subsample periods.

TABLE 1.7

BOX-JENKINS ESTIMATION RESULTS FOR THE MEAN EQUATION OF R_t SERIES
SAMPLE PERIOD OF 12/30/1988-12/30/1998

Model	Variable	Coefficient	Std. Error	t-stat	p- value	Goodness-of-Fit	
MA (1)	ε_{t-1}	0.14	0.02	7.13	0.00***	AIC	-4.010197
						SBC	-4.007948
MA (2)	ε_{t-1}	0.13	0.02	6.87	0.00***	AIC	-4.009700
	ε_{t-2}	-0.02	0.02	-0.81	0.42	SBC	-4.005201
AR (1)	R_{t-1}	0.13	0.02	6.72	0.00***	AIC	-4.008685
						SBC	-4.006435
AR (2)	R_{t-1}	0.14	0.02	6.96	0.00***	AIC	-4.009911
	R_{t-2}	-0.04	0.02	-2.30	0.02**	SBC	-4.005410
ARMA (1,1)	R_{t-1}	-0.07	0.14	-0.51	0.61	AIC	-4.009232
	ε_{t-1}	0.21	0.14	1.51	0.13	SBC	-4.004732
ARMA (1,2)	R_{t-1}	0.39	0.66	0.60	0.55	AIC	-4.008946
	ε_{t-1}	-0.26	0.65	-0.39	0.70	SBC	-4.002196
	ε_{t-2}	-0.07	0.09	-0.88	0.38		
ARMA (2,1)	R_{t-1}	0.27	0.39	0.70	0.49	AIC	-4.009259
	R_{t-2}	-0.06	0.05	-1.22	0.22	SBC	-4.002507
	ε_{t-1}	-0.13	0.39	-0.35	0.73		
ARMA (2,2)	R_{t-1}	-0.48	0.30	-1.59	0.11	AIC	-4.010387
	R_{t-2}	-0.34	0.12	-2.97	0.00***	SBC	-4.001384
	ε_{t-1}	0.62	0.30	2.05	0.04**		
	ε_{t-2}	0.39	0.12	3.15	0.00***		

TABLE 1.8

BOX-JENKINS ESTIMATION RESULTS FOR THE MEAN EQUATION OF R_t SERIES
SAMPLE PERIOD OF 12/31/1998-01/01/2010

Model	**Variable**	**Coefficient**	**Std. Error**	**t-stat**	**p value**	**Goodness-of-Fit**	
MA (1)	ε_{t-1}	0.05	0.02	2.47	0.01***	AIC	-4.038659
						SBC	-4.036583
MA (2)	ε_{t-1}	0.05	0.02	2.49	0.01***	AIC	-4.038076
	ε_{t-2}	0.01	0.02	0.56	0.58	SBC	-4.033924
AR (1)	R_{t-1}	0.05	0.02	2.50	0.01***	AIC	-4.038684
						SBC	-4.036608
AR (2)	R_{t-1}	0.05	0.02	2.48	0.01***	AIC	-4.038057
	R_{t-2}	0.01	0.02	0.45	0.66	SBC	-4.033905
ARMA (1,1)	R_{t-1}	0.16	0.38	0.41	0.68	AIC	-4.038012
	ε_{t-1}	-0.11	0.38	-0.29	0.77	SBC	-4.033860
ARMA (1,2)	R_{t-1}	-0.98	0.02	-61.39	0.00***	AIC	-4.040864
	ε_{t-1}	1.03	0.02	42.06	0.00***	SBC	-4.034635
	ε_{t-2}	0.06	0.02	3.02	0.00***		
ARMA (2,1)	R_{t-1}	-0.92	0.03	-35.01	0.00***	AIC	-4.040851
	R_{t-2}	0.06	0.02	3.01	0.00***	SBC	-4.034623
	ε_{t-1}	0.97	0.02	51.80	0.00***		
ARMA (2,2)	R_{t-1}	-0.99	0.33	-2.99	0.00***	AIC	-4.040168
	R_{t-2}	-0.01	0.33	-0.05	0.96	SBC	-4.031863
	ε_{t-1}	1.04	0.33	3.15	0.00***		
	ε_{t-2}	0.07	0.32	0.22	0.82		

Utilizing these specifications for the mean equations, the various specifications of the GARCH models as applied for the full sample period are used to model the conditional variance equations for both subsample periods. The results of the GARCH models for both subsample periods are shown in Tables 1.9 and 1.10.

2.6.2.1 Results for the Sample Period of 12/30/1988-12/30/1998. Table 1.7 shows the results of the Box-Jenkins estimation method for the mean equation of the ISE National-100 Index returns during the first subsample period. The AR (1) specification on this table is also used to test the Random Walk Hypothesis as discussed earlier and the coefficient for the variable "R_{t-1}" is significant at 1% level. Such significance of the coefficient rejects the null hypotheses of the both, first hypothesis of the study and the random walk hypothesis of the theory. This result is consistent with the full sample period's result.

Table 1.9 provides the details of the GARCH results for the first sample period. All of the coefficients for the GARCH (1, 1) model are significant at the 1% and 5% levels. Thus, the second null hypothesis, once again, is rejected and a significant relationship between the current conditional variance and the past conditional variance is confirmed. In other words, 79% of past volatility is carried over to into the next period's volatility. Moreover, the sum of the ARCH and GARCH coefficients, α_1 and β_1, is less than one which indicates that the conditional variance during the sample period shows long persistence of volatility. Accordingly, the third null hypothesis that presumes no persistency in the volatility of the ISE National-100 Index returns is rejected.

The results for the GARCH-M (1, 1) model reveal that no significant GARCH effect is found for the mean equation of the ISE National-100 Index returns. Therefore, the fourth null hypothesis is failed to reject for this period. However, the significant effect of past volatility on current volatility besides persistent behavior of volatility continues over the sample period.

One of the asymmetry coefficients, μ , stays insignificant for both EGARCH (1,1) and EGARCH-M (1,1) models for the period. Consequently, asymmetric behavior of the ISE National-100 Index return volatility is not significant based on both EGARCH models' results. Since no asymmetric behavior is detected for the volatility, no significant effect of such volatility on the current returns is noticed as well. As a result, the coefficient for the GARCH term in the mean equation, ϕ, is insignificant at all levels. The EGARCH models' results provide no support for the fifth hypothesis of the study for the period under investigation.

Contrary to the EGARCH models, the GJRGARCH (1, 1) and the GJRGARCH-M (1, 1) models find significant 'leverage effect" for the period. The asymmetric behavior that the EGARCH models were not able to detect is now exposed. The leverage coefficient, λ, is significant for both models at the 1% level. As the GJRGARCH (1, 1) model indicates the same magnitudes of unanticipated positive (good news) and negative shocks (bad news) cause unequal amounts of changes in conditional variance. In the case of unanticipated negative shocks, the change in the conditional variance is 0.67 is higher than the change in the conditional variance due to unanticipated positive shocks. Additionally, the coefficient for the conditional variance including such leverage effect is found to be significant in the mean equation at the 1% level. Therefore, the fifth and the sixth null hypothesis are rejected and it is concluded that a significant leverage effect exists for the ISE National-100 Index return volatility.

The results for the sample period show some differences from the full sample results. These differences occur in the significance of some coefficients of the GARCH-M (1, 1), EGARCH (1, 1), and EGARCH-M (1, 1) models. More explanations and implications of these differences will be made in Section 2.7.

The GJRGARCH-M (1, 1) model provides the best model fits for the subsample periods as it did for the full sample period. The coefficients of the GARCH (1, 1), GJRGARCH (1, 1) and GJRGARCH-M (1, 1) models for the period are very close to the full sample period's coefficients for the same model specifications.

2.6.2.2 Results of the Sample Period of 12/31/1998-01/01/2010. There are only two major differences between the findings for the full sample period and findings for the second subsample period: (1) in the EGARCH-M (1, 1) model for the second subsample period, the coefficient for the GARCH term, ϕ, in the mean equation is insignificant, and (2) some slight differences in the magnitudes of the full sample period coefficients and the second subsample period coefficients incur. Other than these two dissimilarities, the results for the second subsample period are exactly in line with the results for the full sample period.

Mentioned dissimilarities in the findings of this sample period compared to the findings of the full sample period do not cause any changes in the rejection status of any of the hypotheses. All of the null hypotheses for the study are rejected for the second sample period as well. Once again, based on the AIC and SBC criteria, GJRGARCH-M (1, 1) model provides the best model fit for the period.

TABLE 1.9
MLE OF THE GARCH MODELS WITH STUDENT'S T DISTRIBUTION OF THE ERROR TERMS ASSUMPTION
SAMPLE PERIOD OF 12/30/1988-12/30/1998

Coefficient	**GARCH (1,1)**	**GARCH-M (1,1)**	**EGARCH(1,1)**	**EGARCH-M (1,1)**	**GJRGARCH (1,1)**	**GJRGARCH-M (1,1)**
1. a	-1.13*** (0.17)	-1.14*** (0.17)	-0.15 (0.39)	-0.16 (0.43)	0.82*** (0.17)	0.70*** (0.00)
2. b	-0.19 (0.15)	-0.20 (0.15)	0.13 (0.15)	0.11 (0.16)	0.11 (0.15)	0.30*** (0.00)
3. c	1.25*** (0.17)	1.26*** (0.17)	0.27 (0.39)	0.29 (0.43)	-0.66*** (0.17)	-0.58*** (0.01)
4. d	0.31** (0.15)	0.32** (0.15)	-0.12 (0.18)	-0.10 (0.19)	-0.22 (0.14)	-0.42*** (0.01)
5. α_0	4.36E-05*** (9.39E-06)	4.57E-05*** (9.69E-06)	-0.65*** (0.09)	-0.66*** (0.09)	0.00*** (1.44E-05)	0.00*** (3.86E-05)
6. α_1	0.18*** (0.02)	0.18*** (0.02)	0.33*** (0.03)	0.34*** (0.03)	0.16*** (0.03)	0.00* (0.00)
7. β_1	0.79*** (0.02)	0.79*** (0.02)	0.94*** (0.01)	0.94*** (0.01)	0.43*** (0.04)	
8. ϕ *(Garch term in the mean eq.)*		0.83 (0.58)		0.99 (0.60)		-45.63*** (3.85)
9. μ			-0.02 (0.02)	-0.01 (0.02)		
10. λ *(Leverage)*					0.67*** (0.14)	0.48*** (0.04)

Goodness-of-fit Measures						
AIC	-4.275737	-4.275783	-4.272015	-4.272072	-4.451933	-4.813600
SBC	-4.257730	-4.255526	-4.251758	-4.249564	-4.431676	-4.791092
Usable observations	2606	2606	2606	2606	2606	2606
Degrees of Freedom	2599	2598	2598	2597	2598	2598

***, **, * Denotes significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses. The sample period is December 30, 1988 to December 30, 1998 for a total of 2606 usable observations. The GARCH (1, 1) model we estimate is: $R_t = aR_{t-1} + bR_{t-2} + c\varepsilon_{t-1} + d\varepsilon_{t-2} + \varepsilon_t$ where $\varepsilon_t = v_t\sqrt{h_t}$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ .GARCH-M (1, 1) is: $R_t = aR_{t-1} + bR_{t-2} + c\varepsilon_{t-1} + d\varepsilon_{t-2} + \phi h_t + \varepsilon_t$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ .EGARCH (1, 1) is: $R_t = aR_{t-1} + bR_{t-2} + c\varepsilon_{t-1} + d\varepsilon_{t-2} + \varepsilon_t$ and $\log h_t = \alpha_0 + \alpha_1(\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}) + \mu(\left|\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}\right| - \eta) + \beta_1 \log h_{t-1}$. "η" is a stable variable. EGARCH-M (1, 1) is: $R_t = aR_{t-1} + bR_{t-2} + c\varepsilon_{t-1} + d\varepsilon_{t-2} + \phi h_t + \varepsilon_t$ and $\log h_t = \alpha_0 + \alpha_1(\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}) + \mu(\left|\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}\right| - \eta) + \beta_1 \log h_{t-1}$. GJRGARCH (1, 1) is: $R_t = aR_{t-1} + bR_{t-2} + c\varepsilon_{t-1} + d\varepsilon_{t-2} + \varepsilon_t$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \lambda D_{t-1}\varepsilon_{t-1}^2$ and GJRGARCH-M (1, 1) is: $R_t = aR_{t-1} + bR_{t-2} + c\varepsilon_{t-1} + d\varepsilon_{t-2} + \phi h_t + \varepsilon_t$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \lambda D_{t-1}\varepsilon_{t-1}^2$.

TABLE 1.10
MLE OF THE GARCH MODELS WITH STUDENT'S T DISTRIBUTION OF THE ERROR TERMS ASSUMPTION
SAMPLE PERIOD OF 12/31/1998-1/01/2010

Coefficient	**GARCH (1,1)**	**GARCH-M (1,1)**	**EGARCH(1,1)**	**EGARCH-M (1,1)**	**GJRGARCH (1,1)**	**GJRGARCH-M (1,1)**
1. a	-0.98*** (0.01)	-0.98*** (0.01)	-0.98*** (0.01)	-0.98*** (0.01)	1.00*** (0.00)	1.00*** (9.97E-05)
2. b	1.03*** (0.02)	1.03*** (0.02)	1.03*** (0.02)	1.03*** (0.02)	-0.91*** (0.02)	-0.91*** (0.01)
3. c	0.06*** (0.02)	0.06*** (0.02)	0.06*** (0.02)	0.06*** (0.02)	-0.09*** (0.02)	-0.09*** (0.01)
4. α_0	3.49E-05*** (7.34E-06)	3.65E-05*** (7.50E-06)	-0.52*** (0.07)	-0.54*** (0.07)	0.000130*** (1.54E-05)	0.000700*** (4.56E-05)
5. α_1	0.13*** (0.02)	0.13*** (0.02)	0.24*** (0.02)	0.24*** (0.02)	0.09*** (0.02)	0.09** (0.003)
6. β_1	0.84*** (0.02)	0.83*** (0.02)	0.95*** (0.01)	0.95*** (0.01)	0.46*** (0.04)	-0.007 (0.01)
7. ϕ *(Garch term in the mean eq.)*		1.35*** (0.56)		0.88 (0.56)		-16.87*** (1.21)
8. μ			-0.10*** (0.02)	-0.09*** (0.02)		
9. λ *(Leverage)*					0.77*** (0.16)	1.46*** (0.12)

Goodness-of-fit Measures						
AIC	-4.360525	-4.362001	-4.371726	-4.371885	-4.537168	-4.862794
SBC	-4.345991	-4.345391	-4.355117	-4.353199	-4.520558	-4.844109
Usable observations	2872	2872	2872	2872	2872	2872
Degrees of Freedom	2866	2865	2864	2864	2865	2864

***, **, * Denotes significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses. The sample period is December 31, 1998 to January 1, 2010 for a total of 2606 usable observations. The GARCH (1, 1) model we estimate is: $R_t = aR_{t-1} + b\varepsilon_{t-1} + c\varepsilon_{t-2} + \varepsilon_t$ where $\varepsilon_t = v_t\sqrt{h_t}$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ .GARCH-M (1, 1) is: $R_t = aR_{t-1} + b\varepsilon_{t-1} + c\varepsilon_{t-2} + \phi h_t + \varepsilon_t$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ .EGARCH (1, 1) is: $R_t = aR_{t-1} + b\varepsilon_{t-1} + c\varepsilon_{t-2} + \varepsilon_t$ and $\log h_t = \alpha_0 + \alpha_1(\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}) + \mu(\left|\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}\right| - \eta) + \beta_1 \log h_{t-1}$. "η" is a stable variable. EGARCH-M (1, 1) is: $R_t = aR_{t-1} + b\varepsilon_{t-1} + c\varepsilon_{t-2} + \phi h_t + \varepsilon_t$ and $\log h_t = \alpha_0 + \alpha_1(\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}) + \mu(\left|\varepsilon_{t-1}^2 / \sqrt{h_{t-1}}\right| - \eta) + \beta_1 \log h_{t-1}$. GJRGARCH (1, 1) is: $R_t = aR_{t-1} + b\varepsilon_{t-1} + c\varepsilon_{t-2} + \varepsilon_t$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \lambda D_{t-1}\varepsilon_{t-1}^2$ and GJRGARCH-M (1,1) is : $R_t = aR_{t-1} + b\varepsilon_{t-1} + c\varepsilon_{t-2} + \phi h_t + \varepsilon_t$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \lambda D_{t-1}\varepsilon_{t-1}^2$.

2.7 Implications and Comparisons

The overall results of the analysis for all periods confirm the first hypothesis of the study. The null hypothesis of the Random Walk Hypothesis (Kendall and Hill, 1953; Malkiel, 1973) is rejected and it is concluded that the current returns or future returns of the ISE National-100 Index can be to some extent explained and predicted by using the information from the past returns. Thus, the weak-form market efficiency is also rejected for the ISE (Fama, 1970). This result is consistent with the results of other studies in the literature that test random walk hypothesis in the ISE (Muradoglu and Unal, 1994; Buguk and Brorsen, 2003; Aga and Kocaman, 2008; Yavuz and Kiran, 2010; Tas and Dursunoglu, 2005; Aktas and Oncu, 2006). In an emerging stock market such as the Istanbul Stock Exchange, it is expected to find interdependencies between the current and the past prices due to relatively smaller volume of the market and less trading activity.

Significant impact of past stock return volatility on current stock return volatility and persistence of past stock return volatility are two commonly accepted facts for most emerging stock markets. The results across all periods reveal that the persistent volatility behavior exists in the ISE and the past conditional variance of the ISE National-100 Index returns significantly affects the current conditional variances. Past volatility and past behavior in the market escalate and the risk process is not randomly distributed like the return process. Therefore, the second and third hypotheses are supported for all periods in the ISE.

The effect of past conditional variance of the ISE National-100 Index returns on the current mean of the ISE National-100 Index returns is positive and significant for full sample period and the second subsample period only. This effect remains positive but insignificant for the first decade, 1988-1998, of the sample period. The findings for the first decade are consistent with the findings of Choudhry (1996), De Santis and Imrohoroglu (1997), and Lee el al. (2001) who also report positive but not statistically significant relationships between stock market returns and conditional variance in most of the emerging stock markets under investigation. Thus, this may be an indication that after the first decade of the full sample period, the ISE starts showing properties that are found in the developed stock markets.

Significant asymmetric behavior for the conditional variance of the ISE National-100 Index returns is found for both, the full sample period and the second subsample period using the EGARCH (1, 1) model. However, the EGARCH (1, 1) model is unable to detect any significant asymmetric behavior in the conditional variance for the first subsample period. Moreover, the EGARCH-M (1, 1) model fails to identify any significant effect of the asymmetric volatility behavior on the mean equation of the ISE National-100 Index returns for both the first and the second subsample periods. Therefore, the null hypothesis for the fifth hypothesis is rejected for the full sample and the second subsample periods, only. However, it is failed to reject for the first subsample period based on the EGARCH model results. The implication of the insignificant asymmetric volatility behavior for the first subsample period may vary. First of all, during that particular decade, the market was just initiated where the volume and the number of participants were relatively lower, which could have made it harder to detect such asymmetric effects. Moreover, the participants were at the beginning of their learning curve. Thus, it would be no surprise that the market participants were either incapable of incorporating information or were just indifferent in their reactions to same magnitudes of sudden good and sudden bad news. However, the second sub-sample period corrects for that asymmetry effect as the coefficients for the EGARCH models all become significant during this period. This indicates strong evidence that the investors started differentiating between the same magnitudes of sudden good and bad news while becoming more loss averse compared to first subsample period. Overall, loss aversion is more pronounced with the significance of the coefficients provided by the EGARCH models. Therefore, when the stock market becomes more nervous, the participants start selling their securities to avoid steeper losses (Tversky and Kahneman, 1991). These explanations are also consistent with the "Prospect Theory", which also explains the curvilinear shape of the utility graph for agents (Kahneman, and Tversky, 1979).

Consistent with the previously detected asymmetric behavior in the conditional variance of the ISE National-100 Index returns, the GJRGARCH (1, 1) and GJRGARCH-M (1, 1) models provide significant coefficients that confirm "leverage effect" for all periods of the sample. In the case of sudden bad news, the change in the conditional variance of the ISE National-100 Index returns is greater than the change in the conditional variance due to sudden good news by 0.7, 0.67, 0.77, respectively for the full sample, first subsample, and the second subsample periods. Moreover, the GJRGARCH-M (1, 1) model results show that the coefficients for the conditional variance variable in the mean equations also reveal a significant relationship between the conditional variance and the mean equations of the ISE National-100 Index returns. Such results are also consistent with the results of some other emerging stock market studies, which find significant leverage effects in the markets under investigation (Siourious, 2002; Panas 1990). Additionally, the GJRGARCH-M (1, 1) model consistently provides the best model fit across all sample periods explaining the interdependencies of the return processes better compared to other GARCH models applied.

2.8 Conclusion

This essay aims to shed some light on the volatility of the Istanbul Stock Exchange, which is an emerging stock market. Many studies have been conducted on modeling stock markets' volatility and analyze its effects on developed stock markets. However, there is still little known about the volatility of the emerging markets such as the ISE. The results give some important insights about the volatility of the ISE to some extent between 12/30/1988 and 01/01/2010. Even though some political and economic highlights and events within the sample period are mentioned, the detailed analysis of social, economic, political and global implications are mostly left to the reader as such analysis is beyond the scope of this research. The main purpose of this study is to model the volatility using GARCH type models and to provide some evidence on the risk-return behavior in the ISE.

Most previous studies on the ISE have focused on testing market efficiency and the evolution of statistical properties of the prices in the ISE. Lack of research in the ISE regarding the volatility of the prices has led me to undertake this study. Main results show that 82% percent of past volatility in the ISE carries over to future volatility and the current returns of the ISE are significantly affected by the past returns. The latter result implicitly rejects the random walk hypothesis for the time period studied which states that stock market prices evolve according to a random walk and thus the future stock prices cannot be predicted. I also find that the ISE responds asymmetrically to the same magnitudes of unanticipated negative and positive shocks. In the case of negative shocks, the volatility of the market is higher than the volatility caused by a same magnitude of positive shocks and the amount of the volatility difference between these two types of shocks is 0.70 in favor of the negative shocks. This result is a clear indication of small investor panic caused by negative shocks. When the two decades in this time period are analyzed, it is also seen that the results of the first decade period show slight differences from the full sample and the second subsample period results in that the EGARCH models are insufficient to detect any significant asymmetric response for this period. Other than this exception, results across all subsample periods and the full sample period show similar characteristics.

There is also indication that the market starts showing some developed stock market features in the second decade of the sample period. As the volume and trading activity increase, I believe the prices in the market will become more independent and will start reflecting more information in the prices. However, the market is still inefficient with strong interdependencies in the prices and the participants are more loss averse compared to developed stock markets.

The results of this study can be utilized by individual and institutional investors, multinational firms, government and policy makers. The risk and return relationship in the ISE is strong and the volatility of the stock returns is definitely a factor that affects the stock returns. The stabilization or control of the volatility may definitely reduce the overall riskiness of the market and such decrease in the risk may serve well to attract more investors and Foreign Direct Investment (FDI) flows to the country which in turn may help the further development and improvement of the stock market. Informational efficiency of the ISE may also reduce the number of arbitrageurs in the market and this may have a positive impact in achieving stock prices that are close to intrinsic values. Then, the market as a whole may become less prone to sudden peaks and drops in the prices.

One extension of this study could be the inclusion of some exogenous variables that will measure the changes in the economic, social, and political environments in Turkey. By doing that, not only will it be possible to analyze the volatility of the ISE, but it will also be possible to identify the causes of the volatility changes in the ISE. This identification will clear out the effects of certain actions in the market on the magnitude of the volatility changes.

CHAPTER III

SENTIMENT AND STOCK RETURNS IN TURKEY

3.1 Introduction

The twentieth century witnessed the development of many widely-used modern finance theories, many of which focus on the determinants of future stock returns. Portfolio theory, asset pricing models such as Capital Asset Pricing and Arbitrage Pricing Models, rational expectations theory, efficient markets hypothesis are just a few to mention. The uncertainty in both future and expected returns has driven many researchers to investigate a pattern among covariance of stock prices, fundamental risk variables of economics and stock returns. However, these models were purely based on the fundamental risk factors and thus were limited to understanding of systematic risks in stock markets. As financial markets evolved to become more interconnected globally, the success of such conventional models began to decline in analyzing the systematic risk, which is believed to be the main driver of asset prices and expected returns. Thus, investor psychology as a possible risk factor started to gain importance in financial markets (Campbell and Cochrane, 2000). Although, the question of whether there is a relationship between the behavior of investors and stock returns has been discussed in the literature since the late 1970s, this relationship still remains largely unsolved. The efforts towards finding answers for this puzzle bring some explanations, but there is still so much to discover in the field.

Asset prices are believed to be driven by both fundamental risk factors and investor sentiment (Baur, Quintero, and Stevens, 1996). Rational expectations theory puts emphasis on the fundamentals, while behavioral theories of asset pricing focus on the investor sentiment.

Investor sentiment represents a degree of the mood for investors and it ranges from bullish (optimistic) to bearish (pessimistic). Likewise, Baker and Wurgler (2006) define investor sentiment as "… A belief about future cash flows and investment risks that is not justified by the facts at hand". However, there is also emerging evidence that these sentiments may also reflect fully rational expectations based on fundamentals, besides an irrational enthusiasm, or a combination of the two (Verma et al, 2006). The latter argument is also in line with Hirshleifer (2001) who implies that the expected returns relate to both risks and investor misevaluation.

Numerous studies have worked on theoretical structures to investigate the dynamics of the relationship between stock returns and investor sentiment (Black. 1986; Trueman ,1988; DeLong, Shleifer, Summers and Waldman, 1990 and 1991; Shleifer and Summers ,1990; Lakonishok, Shleifer and Vishny, 1991; Campbell and Kyle, 1993; Shefrin and Statman, 1994; Palomino, 1996; Barberis, Shleifer and Vishny ,1998; Daniel, Hirshleifer and Subramanyam,1998; Hong and Stein, 1999). One common theme among these studies is the conclusion that a group of investors, named as noise traders, often make investment decisions without the consideration of fundamentals and they are able to affect stock prices with their unpredictable changes in their sentiments. Individual investors are more likely to be these noise traders as they have access to the least privileged information in the market.

The seminal work by Delong, Shleifer, Summers, and Waldman in 1990 carries a great importance in the field as it develops theoretical framework for a noise trader model. In this model, noise traders are claimed to act on their sentiments rather than the fundamental risk factors and their trading activities are considered to distort the stock prices from the intrinsic values. Calafiore et al. (2009), Verma et al. (2008), Brown and Cliff (2004 and 2005), Lee et al. (2002), Fisher and Statman (2000), Clarke and Statman (1998), Solt and Statman (1988), De

Bondt (1993) examine the influence of investor sentiments on stock returns and provide evidence in favor of strong co-movements between individual-institutional investor sentiments on stock returns.

Literature on investor sentiments and stock prices contains inconclusive and conflicting results on whether casual effects are attributable to fundamental risk factors, irrational risk factors, or a mix of both. Prior to Verma et al. (2008) literature assumed that sentiments were completely irrational without conducting any test or modeling to rule out existence of fundamentals driven component (Brown and Cliff, 2004 and 2005: Lee et al.2002). Verma et al. (2008) brings a new framework to the literature that decomposes sentiment into fundamentals driven and irrational components. Additionally, Verma et al (2008) considers the possibility of any cross variable dynamics that may exist between individual and institutional investor sentiments, which was ignored in previous studies. Their study examines the role of sentiments at both individual level and institutional level analyzing their simultaneous impact on U.S. stock market returns.The study concludes that investor sentiment is combination of both fundamentals driven (rational) and irrational risk factors and rational sentiments driven by the fundamentals have a larger impact on stock market returns than that of irrational sentiments. However, the effects of both rational component and irrational component of sentiments on stock returns are significant.

In the essence of Verma et al. (2008), there have been limited number of studies in the literature that have investigated the role of fundamentals driven and irrationality driven investor sentiments on stock returns in emerging stock markets (Calafiore et al., 2009). Analysis of such relationship in emerging markets is critical as these markets, because of the higher possibility of market inefficiencies, may be exposed to more unpredictable changes in sentiments which may cause increased noise trading. As a result of elevated noise trading, higher volatilities triggering higher systematic risks can be produced for these markets. Higher levels of risk, then, may correspond to overall less attractiveness of the market to investors.

The contributions of this research to the existing literature are as follows:

(1) Following the methodologies by Verma et al. (2008) and by Calafiore et al. (2009), this essay decomposes sentiments into both fundamentals driven and irrational components of consumer and business sentiments. The regression model used during decomposition also identifies whether significant relationship exists between the used fundamental economic variables and sentiment. Such decompositions also show how much of the percent change in variance of the sentiments is explained by these explanatory fundamental variables.

(2) This study examines the distinct impacts of fundamentals driven (rational) and irrational sentiments of consumers and businesses on stock returns in an emerging market such as Turkey. Investigating such consumer and business sentiments in an emerging market forms an example to understand other emerging market sentiments as well. Moreover, Turkey is one of the VISTA (Vietnam, Indonesia, South Africa, Turkey, and Argentina) markets which are known as the second generation of emerging markets (Tseng, 2009). The first generation of emerging markets in the literature is the BRIC (Brazil, Russia, India, and China) countries. Similar studies to this study have been only conducted for United States and Brazil. Therefore, undertaking this study will enable readers to compare and contrast the results with the results of the studies on both, developed markets and first

generation emerging markets. Such comparisons may reveal important implications for investors, policy makers, governments, and academic scholars.

(3) This research considers the concurrent impact of consumer and business sentiments on stock returns. Studies in literature mostly model individual and institutional investor sentiments separately, ignoring their possible interaction with each other. However, Verma et al. (2008) shows how simultaneous modeling of both sentiments can provide more complete picture of such interaction and its effects on stock returns. Following their approach, this study also examines the synchronized effects of the consumer and business sentiments on the stock market returns in one model by differentiating between the two types of sentiments.

(4) Previous literature mostly assumes that the changes in investor sentiment cause changes in stock returns. However, latest discussions about the direction of causality offer possible bi-directional causality between the sentiments and past stock returns. Instead of focusing on the unidirectional relationship between sentiments and stock returns, this study investigates possible bi-directional causality at both consumer level and business level.

(5) The effects of anticipated and unanticipated events in finance are treated differently. According to rational expectations theory and efficient markets hypothesis, the response of stock market to unanticipated events matters due two different aspects: speed of information dissemination and accurate valuation of the information (magnitude change in stock prices). Hence, this study focuses on the unanticipated component of sentiments and their effects on stock returns as they may have different implications than the anticipated shocks. Vector Auto-Regression (VAR)

technique is used to investigate the effects of such shocks on the system as a whole by interpreting the results obtained by generalized impulse response functions.

(6) The returns used in the Ordinary Least Squares (OLS) and VAR estimations are continuously compounded monthly stock index returns. Verma et al (2008) and Calafiore et al. (2009) did not utilize any widely used asset pricing models in their return estimations. Thus, some may argue that the same model with returns calculated by asset pricing models may exhibit different results. In order to overcome this possible argument and check the robustness of the results for this study, the Capital Asset Pricing Model (CAPM) calculated returns are used as well as continuously compounded returns. The results obtained by both VAR models are compared to see whether they are robust to differently calculated return series.

3.2 Literature Review

This part surveys the related literature under two sections. The first section establishes a link between noise trading, widely used and accepted risk factors, and stock returns. The distinction between noise and information is made in detail. Evidence on the behavior of noise traders and how such behaviors may influence stock prices is also revealed. Investor sentiment and its drivers are also discussed in this section. The second section focuses on the problem of finding a suitable proxy for investment sentiment. This section lists the previously used proxies to measure investor sentiment. Literature's classification of the direct and indirect measures of investor sentiment is also explained in depth.

3.2.1 Noise Trading, Risk Factors, and Stock Returns

The role of investor sentiment on noise trading in financial markets is first discussed by Black (1986). This study discusses the effects of noise trading in financial markets and distinguishes between information and noise. The term “noise traders” is first used by Black (1986) and Kyle (1985) and it represents a group of investors that have no access to fundamental or accurate information but use speculations instead to make buy/hold/sell decisions in the stock markets based on these speculations. It is implied that the presence of noise in the markets cause inefficiency, but this inefficiency does not impair the trading activity completely. The study by Black (1986) supports that some market participants may use noise as it were information. The reasons of the existence of noise traders have been the topic of interest for some studies. Trueman, (1988) brings legitimate reasons for both noise trading and why it must be an important issue in securities markets. Moreover, possible motivations why anyone would rationally want to trade on noise are discussed in this study.

De Long et al. (1990), demonstrate how a set of investors, noise traders, can impact stock prices in equilibrium. Study reports that deviations from the intrinsic values of stock prices are caused by the changes in investor sentiments, which may introduce a systematic risk in markets. De Long et al. (1990) also illustrate that the risk caused by unpredictable changes in investor sentiments lessens the attractiveness of the markets and diminishes information traders’ advantage to carry out arbitrage. This study develops a cornerstone model, “Noise Traders’ Model”.

Palomino (1996) follows the footsteps of De Long et al. (1990) and develops an imperfectly competitive market model with risk averse investors. In this model, noise traders earn higher returns and achieve higher expected utilities than rational investors. This conclusion is consistent with the earlier literature that finds long-run survival of noise traders. On the other hand, Wang (2001) criticizes De Long et al. (1990) in that their model is static and insufficient to capture long-run survival matters of noise traders. Thus, Wang (2001) introduces a model that takes into account the wealth accumulation process of irrational investors as this accumulation arises from the market competition between rational and irrational investors. The conclusion of the study is that bullish sentiments can endure while bearish sentiments cannot persist in the long run.

In another model, De Long et al. (1991) show how noise traders make their portfolio allocations. This study also illustrates that noise traders can earn higher returns than rational investors and they may survive in terms of wealth gain in the long-run. This long-run success of noise traders occurs despite their excessive risk taking and consumption. All of the findings of De Long et al. (1991) provide evidence that the case against the long-run capability of noise traders is not as clear as normally expected. Moreover, Campbell and Kyle's (1993) model demonstrates that the competitive interaction between noise traders and rational investors influence stock prices substantially. This study also illustrates that noise traders with their non-utility-maximizing nature affect stock prices because their exogenous trading behavior show significant differences from rational investors who are consistently risk averse.

In a different context, Shleifer and Summers (1990) offers an alternative to efficient markets hypothesis (Fama, 1970). This argument emphasizes the role of investor sentiments and limited arbitrage in determining stock prices. The presence of the limited arbitrage assumption in the model is more reasonable than the assumed complete arbitrage in efficient markets hypothesis due to the existence of risky assets in the markets. The implication of such result is that changes in investor sentiments are not fully counteracted by arbitrageurs thus may affect stock returns. Moreover, Lakonishok et al. (1991) finds that institutional investors manipulate stock prices in small markets that consist of stocks with small market capitalization using their powers to influence prices.

As conventional asset pricing models failed to produce plausible explanations regarding the drivers of stock returns, considerations of behavioral aspects within these models gained interest. Shefrin and Statman (1994) develop the behavioral capital asset pricing theory. In this model, they assume an interaction between noise traders and information traders. Focusing on specific cognitive errors, they illustrate that the effect of noise traders in the market depends on the type of these errors. Sentiments of noise traders may distort stock prices and may make markets inefficient.

Another stream of research focuses on the relationship between the risk factors and stock prices. It is important to recognize the efforts of the asset pricing models in incorporating possible sources of risks including economic factors. Many studies emphasize these risk factors while searching for their immediate or indirect impact on stock prices. The most commonly used sources of risks in financial markets include growth rate of the economy, short term interest rates, economic risk premiums, interest rates, inflation, business conditions, performance of market portfolio, and currency fluctuations. These are some of the fundamental variables of economics and finance literature that are widely used in capital asset pricing and risk models and are known to feature essential information of general economy and expectations. The common theme among these sources of rational risk factors is the component of "uncertainty". Given the fact there is no model that perfectly forecasts these variables, the risk basically arises from the uncertain information about their future values.

General tendency of economic growth is usually measured with the changes in Gross Domestic Product or Industrial Production Index (Chen et al., 1986). A number of studies show that the overall welfare of the economy is one of the determinants of stock prices (Fama, 1970; Schwert, 1990a). Short-term interest rate is another fundamental variable of economics and finance literature. Campbell (1991) reports that the changes in the short-term interest rates may directly affect the amount of investments in stocks and bonds. The information in economic risk premium is argued to be extracted by the variations in asset returns. A study by Campbell and Shiller (1987) shows that the term structure of interest rates can be used in predicting excess returns for stocks and bonds. Similarly, Chen et al. (1986) report that differing rates of short and long term bonds affect the sequence value of future payments. In their study, it is suggested that the predictions of interest rates from five to ten year horizons show business cycle patterns. Moreover, Fama (1990) illustrates that the term spread between a 10-year U.S Treasury Bonds and 3-month U.S T-bill reveals information about the upcoming values for a series of economic variables. The same study also implies that the variation in long-term interest rates may cause changes in the portfolio structures of investors. General business condition of a country is another commonly used fundamental variable of economics and finance. The business conditions may show cyclic behavior in the short terms. This change of behaviors in business conditions can be most captured by the spread of returns between corporate bonds and government treasuries (Fama and French, 1989; Keim and Stambaugh, 1986). This spread is called the risk of default. A different proxy to measure the business conditions can be the number of liquidated companies in an economy. Lennox (1999) demonstrates how failing companies affect the general business conditions and economy in a country. Lastly, inflation and currency fluctuations are other widely used fundamental variables. Inflation can be defined as the increase in general level of prices of goods and services. Chen et al. (1986) explain how inflation rate may have an impact on both the discount rates and the magnitudes of future cash flows. Fama and Schwert (1977) use inflation as a hedging tool for various types of assets and find that there is a negative correlation between the common stock returns and inflation rates. Furthermore, Sharpe (2002) reports a negative correlation between the stock valuation and expected valuation and attributes this relationship to the increasing expected inflations. Currency fluctuation is an extensively used economic indicator. Thus, an argument on the significant relationship between the currency fluctuation and stock returns has long been discussed in the literature (Elton and Gruber, 1991). All of the above economic indicators are used in this study as the related fundamental variables that may have impact on sentiments of consumers and businesses, which in turn may affect stock returns as well.

In the light of all discussions in literature, another argument is developed that the investor sentiment can be a function of both, fundamental risk factors and unexplainable investor exuberance. Verma et al. (2008) follow the framework provided by Shleifer and Summers (1990) and Brown and Cliff (2004) where they assume that stock prices are affected by both fundamental and noise components of sentiments. They find that the impact of rational sentiments (fundamental risk factors) on stock market returns is greater than that of irrational sentiments (unexplainable investor exuberance) for the US stock markets. Their results support the economic fundamentals-based arguments of stock returns while providing evidence that the irrational sentiments or the investor error have a significant role in determining stock returns. Calafiore et al. (2009) use the same econometric technique and framework of Verma et al. (2008) and test the impact of rational-irrational sentiments on stock returns for Brazil. Their results confirm significant bidirectional relationship between stock returns and rational component of sentiments. They find no significant effect of irrational components on Brazilian stock returns.

3.2.2 Measures of Investor Sentiment

In general, literature suggests that the random changes in noise traders' sentiment can introduce a systematic risk that is priced in markets. To further investigate this issue, several empirical studies have examined the impact of investor sentiments on stock returns. These studies use either direct or indirect measures of investor sentiments.

Studies using the direct measures of investor sentiment utilize survey based index scores as proxies. Solt and Statman (1988) and Siegel (1992) use the bearish sentiments index, published by Investor Intelligence *("II")* to measure investor sentiment. Solt and Statman (1988) find no significant relationship between the sentiments and stock returns. However, Siegel's (1992) results point a strong concurrent relationship between sentiments and stock returns. Though, the direction of causality between stock returns and sentiments is ignored in this study. Studies by Clarke and Statman (1998) and Lee et al. (2002) are also utilizers of *II* survey data to measure investor sentiments.

American Association of Individual Investors *("AAII")* publishes survey data measuring the feelings and expectations of individual and institutional investors. De Bondt (1993) uses *AAII* survey data and shows a co-movement between small investor sentiments and market. Another approach on the usage of the *II* and *AAII* survey data comes from studies like Fisher and Statman (2000), Brown and Cliff (2004), Brown and Cliff (2005), and Verma et al. (2008). These studies utilize both surveys.. Fisher and Statman (2000) additionally use the Merrill Lynch data to examine investor sentiments and they suggest that AAII, II, and Merrill Lynch survey data can be used to represent the sentiments of individual, institutional, and professional strategist investors, respectively. Brown and Cliff (2004) investigates the causality between stock returns and institutional and individual investor sentiments using II and AAII scores, once again II and

AAII representing institutional and individual investor sentiments, respectively. Furthermore, Calafiore et al. (2009) utilizes another survey data, Consumer Confidence Index ("CCI") and Business Confidence Index ("BCI") scores, as measures of consumer and business sentiments for their study on the relationship between investor sentiments and stock returns in Brazil.

Close-ended fund's discount (Lee et al., 1991; Chan., 1993, Swaminathan, 1996; Elton et al. 1998; Neal et al., 1998; Sias et al., 2001; Gemmill et al., 2002; Baker et al., 2003), market performance-based measures (Brown and Cliff, 2004), trading activity-based measures (Neal and Wheatley, 1998; Brown and Cliff, 2004), derivative variables (Brown and Cliff, 2004), dividend premium (Baker and Wurgler, 2003), and IPO-related measures (Baker and Wurgler, 2003; Brown and Cliff, 2004) are some examples of the indirect measures of investor sentiments. However, whether these proxies are appropriate measures of investor sentiments could be a topic of debate. Moreover, studies that use these proxies show mixed results in terms of relationship between sentiments and stock returns.

Some studies look at the relationship between investor sentiments and stock returns at the individual level. They all find strong co-movements between the individual investor sentiments and stock returns (De Bondt, 1993; Brown and Cliff, 2004; Verma et al., 2008; Calafiore et al., 2009). However, studies in this field show mixed results regarding individual investor sentiments' role in short-term predictability of stock prices (Fisher and Statman, 2000; Brown and Cliff, 2004).Similarly, studies that focus on the relationship between investor sentiments and stock returns at the institutional level also find strong co-movements between institutional investor sentiments and stock returns (Brown and Cliff, 2004, Verma et al., 2008, and Calafiore et al., 2009)) and again provide mixed results regarding institutional investor sentiments' the short-term implications on stock prices (Solt and Statman, 1988; Clarke and Statman, 1998; Lee et al., 2002; Brown and Cliff, 2004). In general, these studies present influential and consistent empirical evidence for us to hypothesize that stock prices are affected by both individual and institutional investor sentiments.

Decomposition of the sentiment variables into components of fundamentals driven sentiment and irrational sentiment has been explored to a very limited degree until Verma et al. (2008). Previous studies usually assume that all trading activities that are induced by sentiments are noise trading. This assumption completely ignores the possibility that some noise traders may also use economic fundamentals technique. Verma et al. (2008) split sentiments-induced trading into two parts: fundamentals-based (rational) and noise-based (irrational) trading. This division implies that not all sentiments may be pure noise. It is possible that part of investor sentiment is based on the technical analysis of economic fundamentals. Calafiore et al. (2009) follow the footsteps of Verma et al. (2008) and decompose the sentiments into rational and irrational components for an emerging market: Brazil.

In short, the literature on the relationship between investor sentiments and stock returns classify investors under two groups: rational or fundamentalist investors make their predictions and judgments using the various fundamental variables whereas speculators or noise traders do not incorporate these fundamentals variables in their decision making processes. Rational investors and speculators may value stocks differently. However, according to the investor psychology approach, the stock prices should reflect weighted average of both values (Hirshleifer, 2001). Moreover, individual investors and institutional investors may both be speculators to some extent and may affect stock prices with random changes in their sentiments. Overall, strong evidence is provided in favor of a contemporary relationship between stock returns and investor sentiment during initial shocks. However, the literature provides mixed results on the progress of such relationship subsequent to these shocks. The literature also provides some evidence that this relationship is attributable to both, rational expectations based on risk factors and investor irrationality in developed stock markets (Verma et al., 2008), whereas investor irrationality has no significant impact on stock returns in emerging stock markets (Calafiore et al., 2009).

3.3 Model

Brown and Cliff (2005), Shleifer and Summers (1990), Verma et al. (2008), and Calafiore et al. (2009) state that sentiments to some extent contain both, rational expectations based on risk factors and investor irrationality. Moreover, Hirshleifer (2001) suggests that expected returns are related to both, rational risk factors and investor misevaluation. Thus, it is expected for stock returns to be affected by both fundamentals and noise components of sentiments. Investor optimism and pessimism could be a rational reflection of future expectation or irrational exuberance or a mix of both. Accordingly, investor sentiments could be decomposed into two parts: (i) rational (fundamentals) component based on the fundamentals and (ii) irrational component based on the noise (Verma et al. 2008).

Consequently, equations (1) and (2) could be formulated to model rational and irrational effects of fundamentals and noise respectively on sentiments of consumers and businesses:

$$ConSent_t = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + \xi_t \qquad \text{(Eq. 2.1)}$$

$$BusSent_t = \theta_0 + \sum_{j=1}^{J} \theta_j Fund_{jt} + \vartheta_t \qquad \text{(Eq. 2.2)}$$

where γ_0 and θ_0 are constants, γ_j and θ_j are the parameters to be estimated; ξ_t and ϑ_t are the random error terms. $ConSent_t$ and $BusSent_t$ represent the shifts in sentiments of consumers and businesses respectively at time *t*. $Fund_{jt}$ is the set of fundamentals representing rational expectations based on risk factors that have been shown to carry necessary information in conditional asset pricing literature. The fitted values of equations (2.1) and (2.2) capture the rational component of sentiments (i.e. $\hat{ConSent}_t$ and $\hat{BusSent}_t$). Additionally, the residuals of equations (2.1) and (2.2) capture the estimated irrational component of sentiments (i.e. $\hat{\xi}_t$ and $\hat{\vartheta}_t$). Based on the above sentiment formulations one could analyze how the stock returns are affected by the decomposed components of sentiments. Equation (2.3) shows how the fundamentals (rational) and irrational components of sentiments, estimated based on equations (2.1) and (2.2), impact the stock returns:

$$R_t = \alpha_0 + \alpha_1 \, \hat{ConSent}_t + \alpha_2 \, \hat{BusSent}_t + \alpha_3 \, \hat{\xi}_t + \alpha_4 \, \hat{\vartheta}_t + \rho_t \qquad \text{(Eq. 2.3)}$$

where α_0 is a constant while α_1, *α2, α3* and *α4 are* the parameters to be estimated; ρ_t is the random error term. Specifically, the parameters α_1 and α_2 capture the effects of fundamentals based (rational) sentiments on the part of consumers and businesses, respectively; while α_3 and α_4 capture the effects of noise based (irrational) sentiments of consumers and businesses, respectively. Vector Auto Regression (VAR) technique is the appropriate technique for the purpose and more information on the appropriateness of VAR models for this study is detailed in the methodology section. A five- variable VAR model is implemented to obtain generalized impulse responses to see the distinct effect of each variable in the vector system.

3.4 Data and Sample

3.4.1 Variables and Descriptive Statistics

This research uses a monthly data from December 2003 to January 2010. The source for the data is DataStream Advance and Central Bank of the Republic of Turkey. The choice of consumer and business sentiments is very similar to Brown and Cliff (2004), Fisher and Statman

(2000), DeBondt (1993), and Verma et al.(2008), and Calafiore et al. (2009), which use the survey data of American Association of Individual Investor (AAII), consumer and business confidence index scores. Therefore, "Consumer Confidence Index" (CCI) and "Business Confidence Index" (BCI) scores are utilized as proxies to measure consumer and business sentiments for Turkey. These surveys are conducted by the Turkish government and they aim to reflect the sensitivity of consumers and businesses to the changes in economic and political environments globally as well as domestically. Thus, *ConSent* and *BusSent* represent CCI scores and BCI scores, respectively.

ISE National-100 Index prices are used to calculate the stock returns. This index represents 90% of the market capitalization in the Istanbul Stock Exchange. The continuously compounded returns for ISE National-100 Index are estimated by DataStream Advance. This index includes first one hundred companies ranked based on size (market capitalization) in the ISE. The name of this variable in the study is "*ISE100*". Returns on the ISE-All Shares Index are used as a proxy for the return on a market portfolio as this index includes all listed shares in the ISE at equal weights. ISE-All Shares Index returns are denoted with "*Rm*", henceforth. All returns are U.S dollar denominated.

Following variables are used to represent the fundamentals as they provide needed information in the asset pricing literature[3]:

(i) Overnight interest rates measured as the effective yield on Turkish deposits (Campbell, 1991 and Calafiore et al., 2009). ("BUSCON")

[3] The market risk premium, which is calculated as the difference between the rate of return on a market portfolio and the risk-free rate, is excluded in the fundamental risk factors variables. Otherwise, the interpretation of the results after application of an asset pricing model, such as CAPM would have been compromised. The question whether the irrational component of sentiments can be explained by the market risk premium is addressed by regressing the market risk premium against the irrational components of sentiments. The coefficients from these regressions are not significant, confirming that the irrational components of sentiments are not significantly affected by the market risk premium. The results of these regressions, both at the consumer and business levels, can be viewed in Appendix B.6.

(ii) The number of companies liquidated per month to measure business conditions (Lennox, 1999). ("COMPANY")

(iii) JP Morgan Emerging Markets Bond Index + Turkey rate is used to measure the specific country risk of Turkey (Calafiore et al., 2009). ("COUNTRISK")

(iv) The terms structure of interest rates calculated as the difference between 90-day interbank interest rate and 30-day interbank interest rate as a proxy for economic risk premium (Ferson and Harvey, 1991; Campbell and Shiller, 1987). (" ECONRISKPRE")

(v) Currency fluctuation measured as the changes in Turkish Lira to US dollar exchange rate index (Verma et al, 2008), (Calafiore et al., 2009). ("EXCHANGE")

(vi) Economic growth as measured by the changes in the Industrial Production Index monthly series (Fama, 1970; Schwert, 1990a; Verma et al., 2008; Calafiore et al., 2009). ("GROWTH")

(vii) Inflation measured as the monthly changes in the consumer price index (Sharpe, 2002; Fama and Schwert, 1977). ("INFTR")

(viii) Terms of trade for Turkey as measured by the monthly ratio between the export price index and the import price index (Calafiore, 2009). ("TOT")

TABLE 2.1

DESCRIPTIVE STATISTICS OF VARIABLES

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
CONSENT	92.61	93.89	111.90	68.88	11.26	-0.37	2.17
BUSSENT	-2.70	4.40	26.60	-69.00	24.40	-1.22	3.60
ISE100	0.01	0.04	0.30	-0.30	0.12	-0.45	3.18
RM	0.02	0.04	0.31	-0.41	0.13	-0.78	4.21
BUSCON	15.86	16.25	26.00	6.50	4.03	-0.22	3.36
COMPANY	766.32	672.00	1670.00	381.00	285.76	1.74	5.32
COUNTRISK	253.10	251.07	337.81	177.87	35.23	0.19	2.71
ECONRISKPRE	0.26	0.17	1.32	-1.39	0.37	-0.38	7.76
EXCHANGE	1.39	1.36	1.69	1.16	0.13	0.10	2.28
GROWTH	0.61	-0.28	22.66	-24.93	8.02	0.03	3.92
INFTR	0.70	0.64	2.60	-0.73	0.72	0.40	2.93
TOT	97.43	97.60	103.82	89.30	3.11	-0.29	2.86

The variables are consumer sentiments (CONSENT), business sentiments (BUSSENT), US dollar denominated returns on the ISE100 index (ISE100), US dollar denominated returns on the ISE-All Share Index used as a proxy for the return on a market portfolio (Rm), business conditions measured by overnight interbank rate (BUSCON) and the number of companies liquidated per month (COMPANY), country risk measured by JP EMBI+Turkey (COUNTRISK), economic risk premium measured by the spread between 90-day interbank rate and 30-day interbank rate (ECONRISKPRE), currency fluctuation measured by the changes in Turkish Lira to US Dollar exchange rate index (EXCHANGE), economic growth measured by the percentage change in industrial production index (GROWTH), , inflation measured by the percentage change in consumer price index (INFTR), terms of trade for Turkey measured by the monthly ratio between the export price index and the import price index (TOT).

Table 2.1 reports the descriptive statistics of the variables used in the study. The mean of *ConSent* is greater than the mean of *BusSent* for the sample period. This suggests that consumers have been more bullish than businesses during the sample period. The monthly mean return for the ISE National-100 Index is 1%. The standard deviations of both, consumer and business sentiments, are much higher than the standard deviation of the ISE National-100 Index returns, suggesting that the sentiments have been more volatile than the ISE National-100 Index returns during the sample period.

TABLE 2.2

CROSS CORRELATIONS OF VARIABLES

	CONSENT	BUSSENT	ISE100	RM	BUSCON1	COMPANY	COUNTRISK	ECONRISKPRE	EXCHANGE	GROWTH	INFTR	TOT
CONSENT	1.00											
BUSSENT	0.85	1.00										
ISE100	0.27	0.44	1.00									
RM	0.27	0.43	0.96	1.00								
BUSCON	0.57	0.27	-0.08	-0.07	1.00							
COMPANY	-0.12	-0.20	0.08	0.11	-0.14	1.00						
COUNTRISK	-0.74	-0.47	0.09	0.09	-0.75	0.16	1.00					
ECONRISKPRE	-0.41	-0.31	-0.15	-0.15	-0.07	-0.03	0.03	1.00				
EXCHANGE	-0.27	-0.09	-0.14	-0.15	-0.28	-0.05	0.01	0.39	1.00			
GROWTH	0.09	0.14	0.02	0.03	-0.07	-0.27	-0.02	-0.04	0.01	1.00		
INFTR	0.00	0.01	-0.11	-0.13	-0.01	-0.16	0.05	-0.16	0.00	0.12	1.00	
TOT	0.65	0.69	0.37	0.37	0.15	-0.08	-0.36	-0.32	-0.08	0.08	-0.25	1.00

The variables are consumer sentiments (CONSENT), business sentiments (BUSSENT), returns on ISE100 index (ISE100), returns on ISE market portfolio (Rm), business conditions (BUSCON), the number of companies liquidated (COMPANY), country risk (COUNTRISK), economic risk premium (ECONRISKPRE), currency fluctuation (EXCHANGE), economic growth (GROWTH), , inflation (INFTR), and terms of trade (TOT).

The cross-correlations between stock market returns, sentiment variables, and the fundamentals are shown in Table 2.2. The correlation between consumer and business sentiments is 0.85. This correlation is higher than what previous studies found in similar studies in both, developed and emerging markets. This high correlation shows that consumer and business sentiments in Turkey are highly interrelated and there are possible feedback effects between the two. This result strengthens the previous argument of modeling them jointly in a multivariate setting rather than using isolated modeling for each sentiment. The correlation between the business sentiment and ISE National-100 Index returns is 0.44 which is higher than the correlation between the consumer sentiment and the ISE Natioanl-100 Index returns of 0.27. This may indicates that business investors are more active as noise traders than consumer investors, which is contrary to what previous studies, focusing on developed stock markets, have found. One important reason for this conflicting indication could be that emerging stock markets have fewer consumer investors than developed stock markets. Majority of the correlations among fundamental variables are at acceptable levels, which suggests that each variable represents a unique risk.

3.4.2 Unit Root Tests

It is essential to check the time series properties of each variable before applying econometric techniques. Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979, 1981) to check for unit-roots is performed on each variable. The results of the ADF test are shown in Table 2.3. Considering the loss in degrees of freedom and asymptotically efficient Akaike Information Criteria (AIC) and Schwarz Bayesian Criteria (SIC) (Diebold, 2003), the appropriate number of lags is determined to be two. Moreover, it is checked whether there is a need to include a drift term in the equation. The ADF test results with a drift term included in the equation reveal the same results as there was no drift term (Dolado et al., 1990). As a result, the null hypothesis of the ADF test is rejected for all variables and the variables are stationary and ready for further econometric techniques to be applied. Table 2.3 shows the results of the unit root tests for all variables in the study.

TABLE 2.3

UNIT ROOT TESTS

	Level	First Difference	ADF test results
CONSENT		X	-5.70***
BUSSENT		X	-6.25***
ISE100	X		-7.50***
RM	X		-7.27***
BUSCON		X	-5.44***
COMPANY	X		-4.76***
COUNTRISK		X	-8.90***
ECONRISKPRE	X		-5.27***
EXCHANGE		X	-7.38***
GROWTH		X	-11.30***
INFTR		X	-6.57***
TOT		X	-7.84***
Test critical values:1% level			-3.53
5% level			-2.90
10% level			-2.59

***, **, * Denotes significance at the 1%, 5%, and 10% levels, respectively. The variables are consumer sentiments (CONSENT), business sentiments (BUSSENT), returns on ISE100 index (ISE100), returns on ISE market portfolio (Rm), business condition (BUSCON), the number of companies liquidated (COMPANY), country risk (COUNTRISK), economic risk premium (ECONRISKPRE), currency fluctuation (EXCHANGE), economic growth (GROWTH), , inflation (INFTR), and terms of trade (TOT). The symbol "X" indicates the rejection of the null hypothesis for the ADF test either at the level or first difference for each variable.

3.5 Econometric Methodology and Models

The econometrics methodology applied in this study consists of two major steps. First, an Ordinary Least Squares regression model is performed to decompose the consumer and business sentiments into their fundamentals driven and irrationality driven components. Second, a Vector Auto Regression is utilized to observe the distinct effect of each sentiment variable and the ISE National-100 Index returns on the system as a whole. Next two subsections focus on the OLS regression models and the VAR model applied in the study, respectively.

3.5.1 Ordinary Least Squares Regression Models

Equations (2.1) and (2.2) are run in order to decompose consumer and business sentiments into fundamentals-based (rational) and irrational components. The fitted values of equations (2.1) and (2.2) represent the fundamentals-based (rational) components of sentiments whereas the residuals of the equations (2.1) and (2.2) represent the irrational components of sentiments. Two separate OLS regressions based on equations (2.1) and (2.2) are estimated. Fairly low correlations among variables as shown in Table 2.2 indicate that multicollinearity is not an issue. Tables 2.4 and 2.5 report the results of the OLS regressions. Table 2.4 details that the consumer sentiments are significantly affected by business conditions, country risk, currency, and inflation. Similarly, Table 2.5 reports that the business sentiments are significantly related to business conditions, number of liquidated companies, currency, economic risk premium, economic growth, and inflation. Seven out of eight fundamental variables included in the second OLS regression model have significant effects on the business sentiment in Turkey. This is a clear indication that the variables are well-chosen and have high predictive powers in the model. The fitted values of the Equations 2.1 and 2.2 are named as *"RATIONALCONSUMER"* and *"RATIONALBUSINESS"* as these values represent the fundamentals driven components of the sentiments. Likewise, the residuals from the same equations are designated the names of *"IRRATIONALCONSUMER"* and "*IRRATIONALBUSINESS"* as they correspond to the irrationality driven components of the sentiments. The results provided in Tables 2.4 and 2.5 are consistent with the argument of Brown and Cliff (2005) that investor sentiments may contain a mix of both, fundamentals driven and noise driven components.

TABLE 2.4

EFFECTS OF FUNDAMENTALS ON CONSUMER SENTIMENT

Dependent Variable: CONSENT				
	Coefficient	SE	t-Statistic	Prob.
BUSCON	-1.03	0.35	-2.93	0.005***
COMPANY	-2.37E-04	8.91E-04	-0.27	0.790
COUNTRISK	0.08	0.03	2.70	0.009***
EXCHANGE	-9.93	3.94	-2.52	0.014**
ECONRISKPRE	-0.22	0.68	-0.33	0.744
GROWTH	-0.02	0.03	-0.80	0.425
INFTR	-0.63	0.36	-1.76	0.084*
TOT	0.11	0.16	0.71	0.478
γ_0	-0.17	0.82	-0.20	0.841
R-squared	0.45			
AIC	4.32			
Schwarz criterion	4.60			
Sum squared residuals	241.40			
Log likelihood	-144.19			
F-statistic	6.32			
Prob(F-statistic)	0.00			

***, **, * Denotes significance at the 1%, 5%, and 10% levels, respectively. The variables are consumer sentiment (CONSENT), business conditions (BUSCON), the number of companies liquidated (COMPANY), country risk (COUNTRISK), currency fluctuation (EXCHG), economic risk premium (ECONRISKPRE), economic growth (GROWTH), inflation (INF), and terms of trade (TOT).

$$ConSent_t = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + \xi_t$$

TABLE 2.5

EFFECTS OF FUNDAMENTALS ON BUSINESS SENTIMENT

Dependent Variable: BUSSENT

	Coefficient	Std. Error	t-Statistic	Prob.
BUSCON	-2.04	1.10	-1.85	0.069*
COMPANY	-4.92E-03	2.80E-03	-1.76	0.084*
COUNTRISK	0.35	0.09	3.93	0.000***
EXCHANGE	-25.00	12.37	-2.02	0.048**
ECONRISKPRE	3.77	2.14	1.76	0.083*
GROWTH	0.22	0.10	2.27	0.027**
INFTR	-2.21	1.12	-1.96	0.054*
TOT	0.63	0.49	1.30	0.200
θ_0	2.61	2.59	1.01	0.317

R-squared	0.49
AIC	6.60
Schwarz criterion	6.89
Sum squared residuals	2376.94
Log likelihood	-225.38
F-statistic	7.56
Prob(F-statistic)	0.00

***, **, * Denotes significance at the 1%, 5%, and 10% levels, respectively. The variables are business sentiment (BUSSENT), business conditions (BUSCON), the number of companies liquidated (COMPANY), country risk (COUNTRISK), currency fluctuation (EXCHANGE), economic risk premium (ECONRISKPRE), economic growth (GROWTH) , inflation (INFTR), and terms of trade (TOT).

$$BusSent_t = \theta_0 + \sum_{j=1}^{J} \theta_j Fund_{jt} + \vartheta_t$$

3.5.2 Vector Auto Regression (VAR) Models

Brown and Cliff (2004 and 2005), Lee et al. (2002), Verma et al. (2008) and Calafiore et al. (2009) suggest that there may be an interaction between stock market returns and investor sentiments. Vector Auto Regression (VAR) is found to be the most suitable econometric approach for this research as it enables to investigate the postulated relationships.

According to efficient markets hypothesis of finance, stock markets should only react to the unanticipated component of explanatory variables (Fama, 1970). All variables in a multi index model must be surprises or innovations and they should not be predicted from their past values. (Elton and Gruber, 1991) Hence, asset pricing models employ unanticipated innovations of explanatory variables. Because the formulated models in this research are multi-index models, direct estimation using their present form would only give the relationships between anticipated components and would ignore the effect of changes in the unanticipated components of investor sentiments and stock market returns. Such an approach would bias the results. To overcome this problem in the estimation process, usage of impulse response functions generated from the VAR model is extremely useful. Moreover, VAR models have been shown to be better than the structural models as they have stronger prediction power (Litterman and Supel, 1983; Hakkio and Morris, 1984; Litterman, 1986; Lupoletti and Webb, 1986; Webb, 1999).

Another important aspect to consider is related to the transmission of information contained in the stock prices. This transmission may not be simultaneous for both components of sentiments. Fundamentals-based (rational) and irrational components of investor sentiments may be exposed to different delays in the markets. These delays may cause lags between the observation of data concerning such variables and the incorporation of this information to stock prices. Thus, if all variables in the model are measured at time *t*, this model may be unrealistic due to ignorance of such information delays. In order to eliminate problem, Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) are used to determine appropriate lag lengths for information delays. These criteria help us to identify the optimal lag length for the model and the optimal lag length is found to be two. The general expression of the VAR model is:

$$Z(t) = C + \sum_{s=1}^{m} A(s) + Z(t-m) + \omega(t) \qquad \text{(Eq. 2. 4)}$$

where $Z(t)$ represents a column vector of variables under consideration, C is the deterministic component comprised of a constant, $A(s)$ is a matrix of coefficients, m is the lag length and $\omega(t)$ is a vector of random error terms. The VAR model specification provides advantages when doing policy simulations and integrating Monte Carlo methods to find confidence bands around the point estimates (Genberg et al., 1987; Doan, 1988; Hamilton, 1994). Impulse response functions that are obtained from VAR models are extremely useful tools to see the likely response of one variable to a one time unitary shock in another variable, when all else in the model remain constant. Given that the impulse responses are nonlinear functions of the estimated parameters, confidence bands are formed around the mean response using the Monte Carlo methods (Doan and Litterman, 1986). When the upper and lower bands carry the same sign, impulse responses are considered to be statistically significant at the 95% confidence level. The generalized impulses technique that is described by Pesaran and Shin (1998) are used as the orthogonal set of innovations do not depend on the variable ordering in this technique. Such technique is also superior than the traditional orthogonalized forecast error variance decomposition results based on the widely used Choleski factorization of the VAR innovations as these innovations may be sensitive to variable ordering (Pesaran and Shin, 1996; Koop et al., 1996; Pesaran and Shin, 1998).

In order to examine the relative effects of fundamentals driven (rational) and irrational consumer and business sentiments on stock market returns, a five-variable VAR model with two lags is performed and the general expression for this model is depicted in the equation (2.3). The variables for the VAR model are: ISE National-100 Index returns *(ISE100),* fundamentals driven (rational) sentiments of consumers and businesses *(RATIONALCONSUMER* and *RATIONALBUSINESS),* and irrational sentiments of consumers and businesses *(IRRATIONALCONSUMER* and *IRRATIONALBUSINESS).* Latter four variables are the ones that are generated by the fitted values and residuals of equations 2.1 and 2.2. [4] Sims (1980) and Enders (2003) indicate that autoregressive systems such as the VAR model utilized in this work are difficult to describe in a few words and it is even more difficult to make sense of them by analyzing the coefficients provided by the estimates. Furthermore, the t-tests on individual coefficients are not very reliable guides as they do not fully capture the important interrelationships among the variables.. Therefore, Sims (1980) suggests focusing on the system's response to typical random shocks (impulse response functions-IRFs). In the light of previous findings on autoregressive systems and VAR models, refrain from interpreting the individual coefficients of the VAR model, but rather focus on the relevant effects of IRFs.

3.6 Results of the VAR Model

Figures 2.1(a) and (b) show the impulse responses of the ISE National-100 Index returns to a one-time SD increase in the fundamentals driven (rational) and irrational sentiments of consumers, respectively. As seen in the Figure 2.1(a), the effect of the rational component of consumer sentiment on the ISE National-100 Index returns is positive and significant for the first three months and it becomes insignificant thereafter. However, the effect of the irrational component of consumer sentiment on the ISE National-100 Index returns remains insignificant at

[4] The results of the VAR estimate are presented in the Appendix B.1.

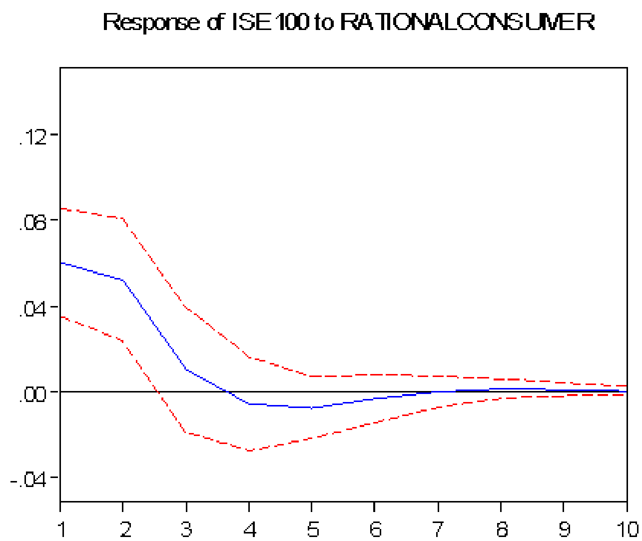
all times during the sample period as shown in Figure 2.1(b). Thus, the response to the rational component is much greater than the response to the irrational component. This may indicate that a positive rational sentiment creates a tendency to increase returns. This result also provides evidence that investor sentiment is not fully irrationality-based. There is a good portion of the sentiment that is fundamentals driven.

Figures 2.2(a) and (b) exhibit the impulse responses of the ISE National-100 Index returns to a one-time SD increase in the fundamentals driven (rational) and exuberance irrational components of business sentiment, respectively. Similar to the results at the consumer level, the impulse response of the ISE National-100 Index returns to a one-time SD increase in the rational component of business sentiment is positive and significant for the first three months and it becomes insignificant thereafter. Once again, the impulse response of the ISE National-100 Index returns to a one-time SD increase in the irrational component of business sentiment is insignificant at all times during the sample period.

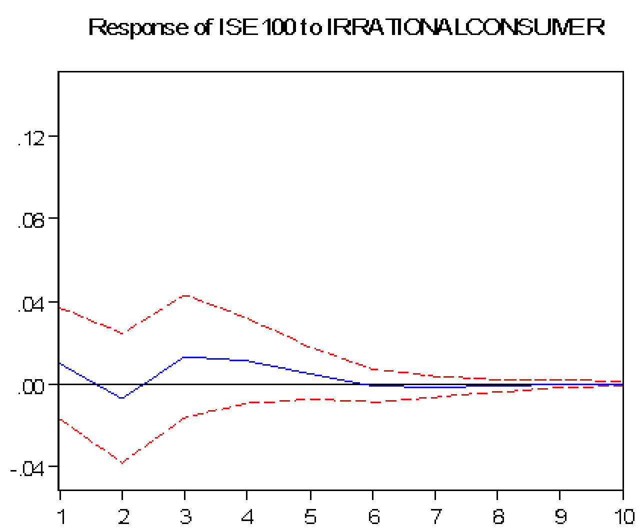
FIGURE 2.1

Response of the ISE National-100 Index Returns to the (a) Rational and (b) Irrational Sentiments of Consumers

(a)



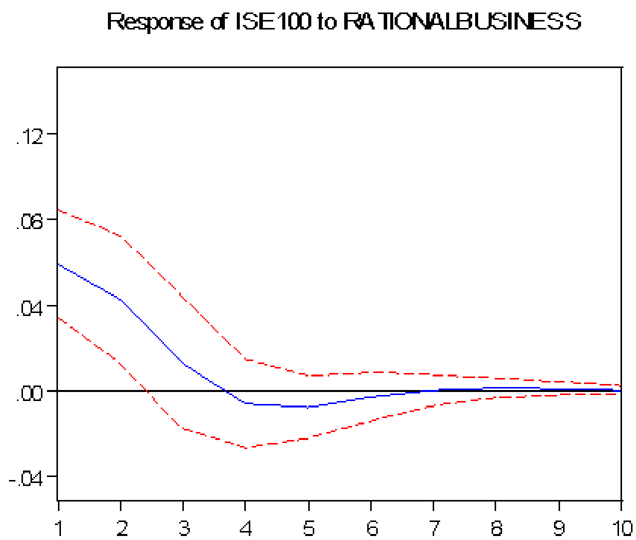
(b)



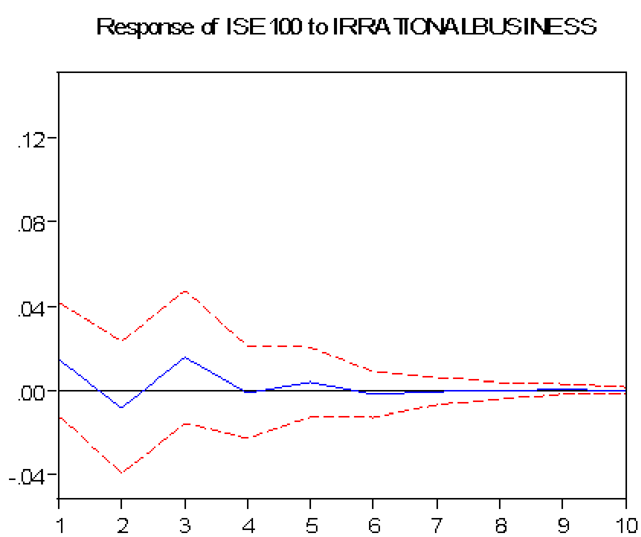
The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant. On each graph, "percentage returns" are on the vertical and "horizon" is on the horizontal axis.

FIGURE 2.2
Response of the ISE National-100 Index Returns to the (a) Rational and (b) Irrational Sentiments of Businesses.

(a)



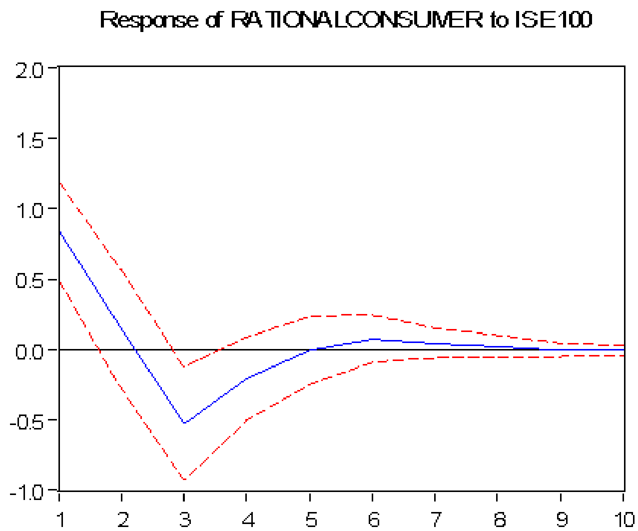
(b)



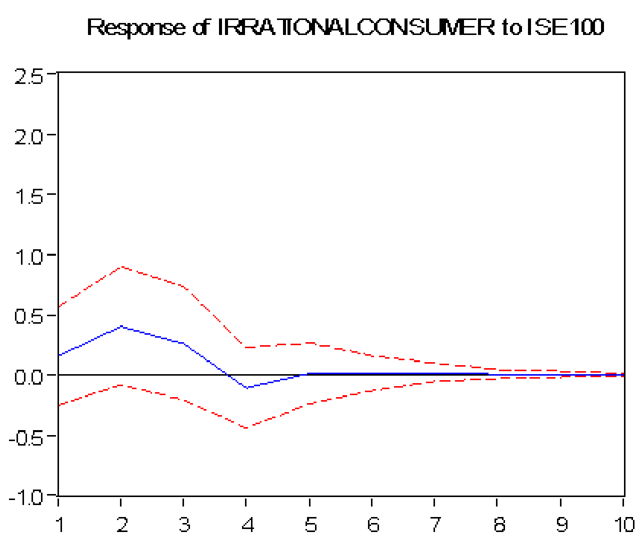
The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant. On each graph, “percentage returns” are on the vertical and “horizon” is on the horizontal axis.

FIGURE 2.3
Response of the (a) Rational and (b) Irrational Sentiments of Consumers to the ISE National-100 Index Returns

(a)

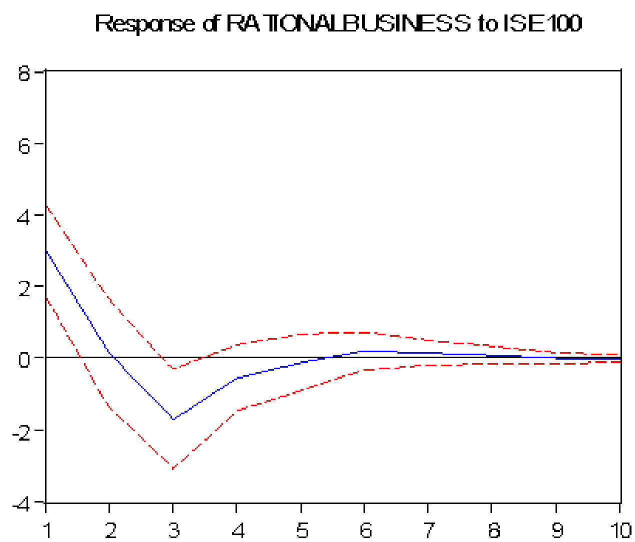


(b)

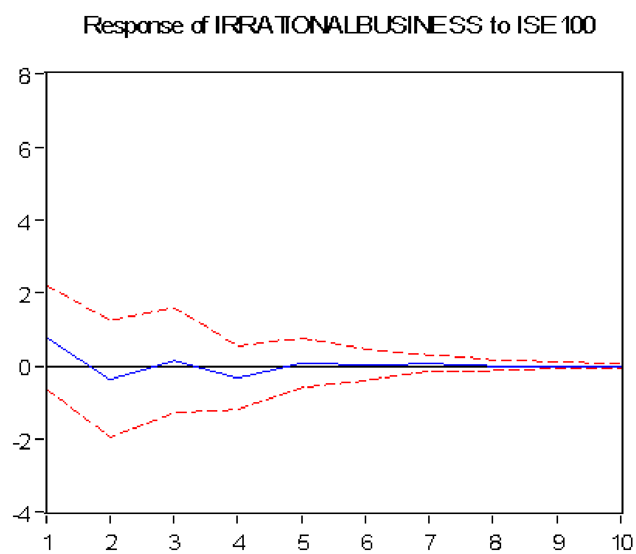


The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant. On each graph, “percentage returns” are on the vertical and “horizon” is on the horizontal axis.

FIGURE 2.4
Response of the (a) Rational and (b) Irrational Sentiments of Businesses to ISE National-100 Index Returns
(a)



(b)



The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant. On each graph, "percentage returns" are on the vertical and "horizon" is on the horizontal axis.

The impulse responses of rational and irrational components of consumer sentiments to a one-time SD increase in the ISE National-100 Index returns are shown in Figures 2.3(a) and (b), respectively. Likewise, Figures 2.4(a) and (b) show the impulse responses of rational and irrational components of business sentiments to a one-time SD increase in the ISE National-100 Index returns. As seen in Figures 2.3(a) and 2.4(a), the impulse responses of rational sentiments of consumers and businesses to a one-time SD increase in the ISE National-100 Index returns are positive and significant for the first three months and it becomes insignificant thereafter. On the other hand, the impulse responses of irrational sentiments of consumers and businesses to a one-time SD increase in the ISE National-100 Index returns remain insignificant at all times during the sample period as seen in Figures 2. 3(b) and 2.4(b). These findings may mean that the rational components of sentiments, both at the consumer and business levels, are affected positively and significantly by the increases in the ISE National-100 Index returns. The ISE National-100 Index price increases may indicate a good economic habitat and it may be reflected in the fundamental variables used in the study. Thus, it becomes as a natural outcome that fundamentals-based analysis show this impact on the sentiments more severely.

In summary, a significant bidirectional relationship between returns and rational component of consumer and business sentiments is confirmed and the results do not show any significant differences between consumer and business levels. The findings are consistent with Calafiore et al. (2009), which focuses on another emerging market: Brazil. Their study also confirms significant bidirectional relationship between stock returns and rational components of consumer and business sentiments. They find no significant effect of irrational components on Brazilian stock returns.

However, both, the results of this study and that of Calafiore et al. (2009), only partially agree with Verma et al. (2008). Contrary to Verma et al. (2008), Calafiore et al. (2009) and this study do not find any significant effect in favor of irrational sentiments. Such disparity could be attributed to the differences between developed and emerging stock markets as Verma et al. (2008) focus on US stock markets. In contrast to developed stock markets, institutional investors play more major role in shaping emerging stock market movements than individual investors. Institutional investors are known to utilize more technical and analytical analysis in their decision- making processes. It may be implied that as the number of individual investors increase and they become more active participants, irrational components of sentiments in emerging stock markets may become significant following the trails of their developed counterparts.

3.7 Relationship between CAPM Estimated Excess Returns and Sentiments

Some might argue that the ISE National-100 Index returns included in the VAR estimations are continuously compounded returns, which are not calculated or fitted with any of the widely used asset pricing models of the finance literature. Asset pricing models such as Capital Asset Pricing Model (CAPM) (Sharpe, 1964) and Arbitrage Pricing Model (APT) (Ross, 1976) enable stock market participants to predict future expected returns to some extent. Thus, in order to handle such limitation of the stock price index returns included in the previous VAR model, the CAPM generated excess returns are estimated for the ISE National-100 Index. Then, another five- variable VAR model is run to check the robustness of the previous results in the above section. The regression estimation for the Capital Asset Pricing Model is generally expressed as below (Ruppert, 2004):

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,t}(R_{m,t} - R_{f,t}) + \rho_t \qquad \text{(Eq. 2.5)}$$

Where $R_{i,t} - R_{f.t}$ is the excess return on the capital asset, it is the excess return of the ISE National-100 Index at time *t* in this study, R_f is the risk-free rate of interest such as interest arising from government bonds at time *t*, β_i (the beta) is the sensitivity of the expected excess asset returns to the expected excess market returns, and $R_{m,t} - R_{f,t}$ is the excess return of the market portfolio that contains every security in the market with the actual weights at time *t*.

The Capital Asset Pricing Model requires a risk-free rate of return: a rate of return for a riskless asset in the market. Unfortunately, there are no monthly series exists for a possible risk-free rate substitute for Turkey. Thus, a proxy for the risk-free rate should be found or created. There are some widely used proxies for such risk-free rate for Turkey. One of the proxies is to use the below formula and calculate the risk-free rate (Gursoy and Rejepova, 2007):

$$RF^* = USTBILL + (INFTR - INFUS) + USTBILL\,(INFTR - INFUS) \qquad \text{(Eq. 2.6)}$$

Where *RF** is estimated monthly Turkish risk-free rate, USTBILL is monthly equivalent of 3-monthU.S T-Bill rate, *INFTR* is monthly inflation rate in Turkey, and *INFUS* is monthly inflation rate in U.S. Monthly inflation rate series. The monthly inflation rate series for Turkey is calculated by using the below estimation method (Fama and Schwert, 1977):

$$INFTR = \log(CPI_t / CPI_{t-1}) \qquad \text{(Eq. 2.7)}$$

Where *INFTR* is the monthly inflation rate in Turkey, and *CPI* is the monthly scores of Consumer Price Index for Turkey. The logarithmic differences of the *CPI* series give the monthly inflation rate series for Turkey. However, another and simpler used proxy for the risk-free rates in the literature is using the inflation rates alone (Bekaert and Engstrom, 2010;

Damodaran, 2008).Thus, the estimated risk-free rate series *(RF*)* and the inflation rate series *(INFTR)* for Turkey are compared against each other. The descriptive statistics and the results of the normality tests for both series can be found in Appendix B.2. Figure 2.5 provides an evidence for the strong co-movement of the both series. Although, both, the estimated risk free rate based on the formula and the inflation rate, are good proxies for the risk-free rate in the CAPM estimation, the estimated risk-free rate is used for this study.[5]

Another important consideration on calculating the CAPM driven returns is whether to include an intercept term in the model. Some argue that the intercept term would be unnecessary (Ruppert, 2004).The intercept term in a CAPM model, theoretically, should be equal to zero as CAPM is an equilibrium model. However, in reality, the intercept term is usually allowed in the model as it serves to detect any mispricing of securities. The sign and magnitude of the intercept term gives an idea about the direction and the strength of the mispricing. Therefore, the CAPM driven returns are estimated with an intercept term in the model[6].

CAPM Model

$$(R_{i,t} - R_{f,t}) = \alpha_{0,t} + \beta_{1,t}(R_{m,t} - R_{f,t}) + \nu_{1,t} \qquad \text{(Eq. 2.8)}$$

Where $\alpha_{0,t}$ and $\beta_{1,t}$ are the parameters to be estimated and $\nu_{1,t}$ is the error term. $R_{i,t}$ is the continuously compounded monthly ISE National-100 Index return series. R_m is the continuously

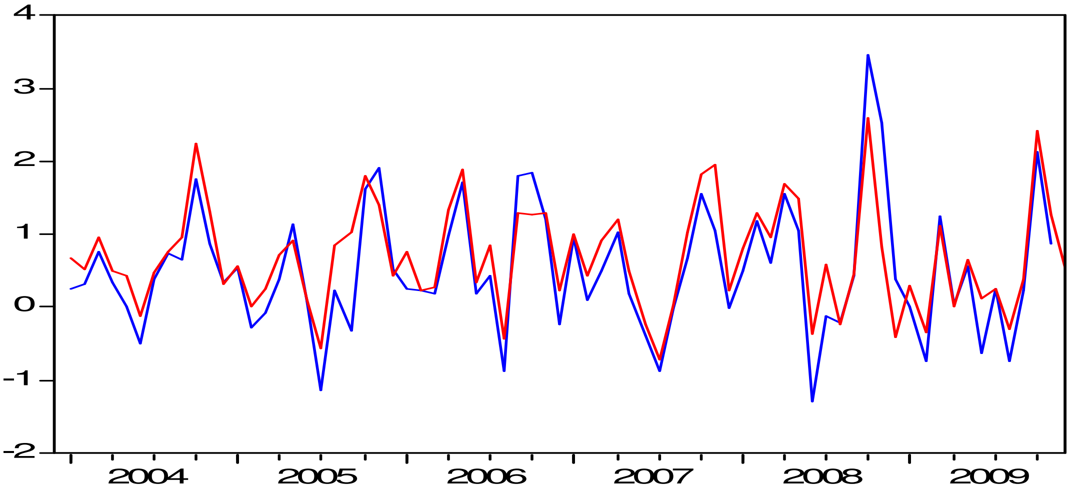
[5] The ISE National-100 Index excess return series are calculated using the CAPM model. Two CAPM models are separately run using the two proxies in the literature for the risk-free rate: inflation rate and the estimated risk-free rate based on formula in Equation 2.6. No statistical significance is found between the results provided by the two CAPM models. The CAPM fitted excess returns are also obtained from both models and these returns are used in separate Vector Auto Regression (VAR) models for robustness check. Once again, the results of the VAR models show no significant differences. Thus, the CAPM model that uses the estimated risk-free rate is used for the rest of the study and the results reported are based on this proxy.

[6] The CAPM estimation in Equation 2.8 exhibits an intercept term that has a negative sign but no statistical significance in the equation. Such negative sign of the intercept term in the CAPM model indicates a mispricing of the security, particularly underpricing of security in this case. However, the magnitude of the underpricing remains insignificant (Ruppert, 2004). The OLS results of CAPM regressions can be found in Appendix B. 3.

compounded monthly ISE All Share Index return series that is used as a proxy for the return on a market portfolio that consists of all stocks in the Istanbul Stock Exchange. The monthly risk-free rate series for Turkey (R_f) is estimated using the formula in Equation 2.6.

FIGURE 2.5

Estimated Risk Free Rate vs. Inflation Rate



Then, the CAPM regression is run by using Equation (2.8) with the OLS method and the fitted values of this regression are obtained. The fitted values of the CAPM model are named as *"CAPM"*[7].

3.7.1 Results of the VAR Model with the Estimated CAPM Excess Returns

The left hand side of equation 2.8 represents the excess returns of the ISE National-100 Index returns over the estimated risk free rate of return. This part reflects the risky return

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[7] Another CAPM model with no intercept term is run using the following equation (Equation 2.9): $(R_{i,t} - R_{f,t}) = \beta_{2,t}(R_{m,t} - R_{f,t}) + v_{2,t}$ The fitted values of the CAPM models in Equations 2.8 and 2.9 are compared and no statistically significant results are found between the values. Therefore, the five-variable VAR model, expressed in Equation 2.3, is run using the fitted values of first CAPM model in Equation 2.8.

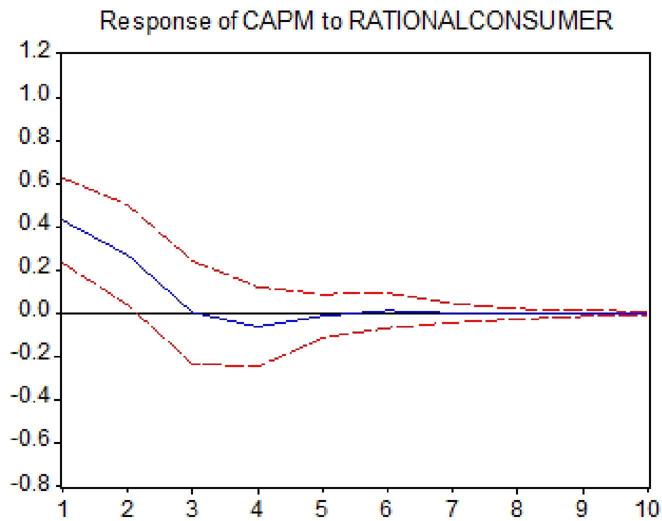
component of the ISE National-100 Index. The difference between the return on the market portfolio and the estimated risk free rate of return is included in the right hand side of the equation. This part is the risky return component of the market portfolio, or market risk premium, in the ISE as well. The coefficient beta shows the relationship between the excess returns of the ISE National-100 Index and the market risk premium. The coefficient beta is positive and significant at 1% level. The value of the beta coefficient is 0.99.If the value of this coefficient were 1, then it could be concluded that the excess returns of the ISE National-100 Index moves exactly same with the market portfolio. However, the value of 0.99 shows that the relationship between the two excess returns is still extremely strong and significant.

The five-variable VAR model is run using CAPM model fitted excess returns, rational sentiments of consumers and businesses, and irrational sentiments of consumers and business. The results at the consumer and business levels do not show any significant differences. Figures 2.6 (a) and (b) and 2.7 (a) and (b) show the generalized impulse response functions graphs for the effects. The response of the CAPM fitted excess returns to a one-time SD increase in rational components of sentiments are positive and significant for the first three months and becomes insignificant thereafter. However, the response of the CAPM fitted excess returns to a one-time SD increase in the irrational components of sentiments is insignificant at all times.

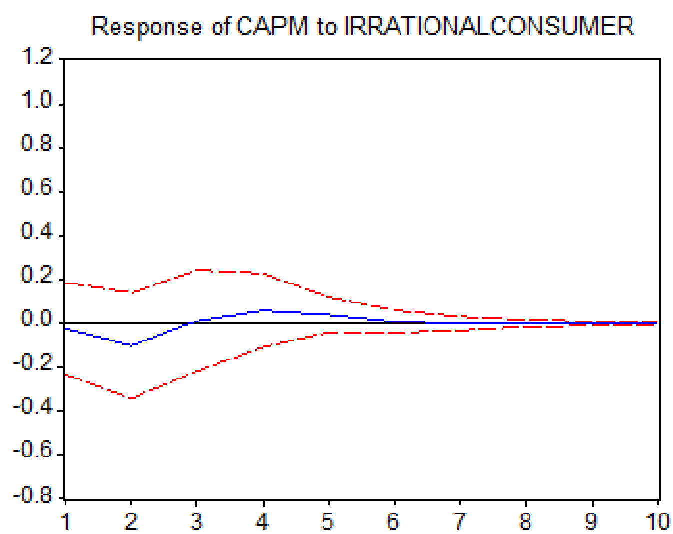
The responses of rational components of sentiments to a one time SD increase in CAPM fitted excess returns are positive and significant for the first two months as seen in Figures 2.8(a) and 2.9(a). However, the responses of the irrational components of sentiments to the same SD increase in CAPM fitted excess returns are insignificant at all times (See Figures 2.8(b) and 2.9(b)).

FIGURE 2.6
Response of the CAPM Returns to the (a) Rational and (b) Irrational Sentiments of Consumers

(a)

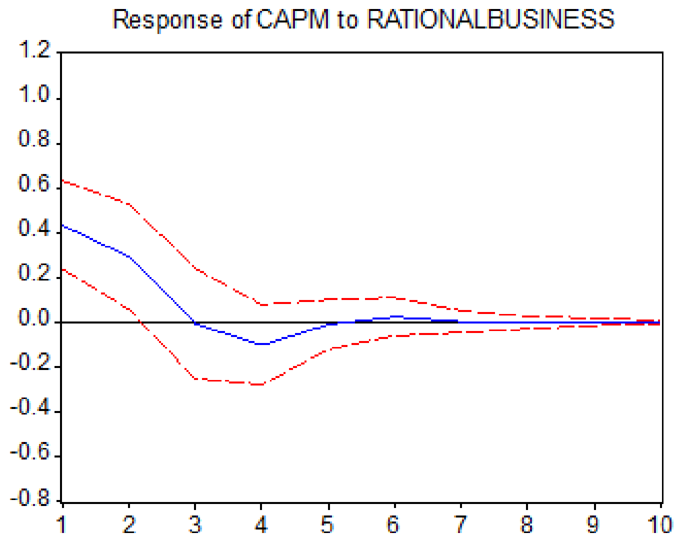


(b)

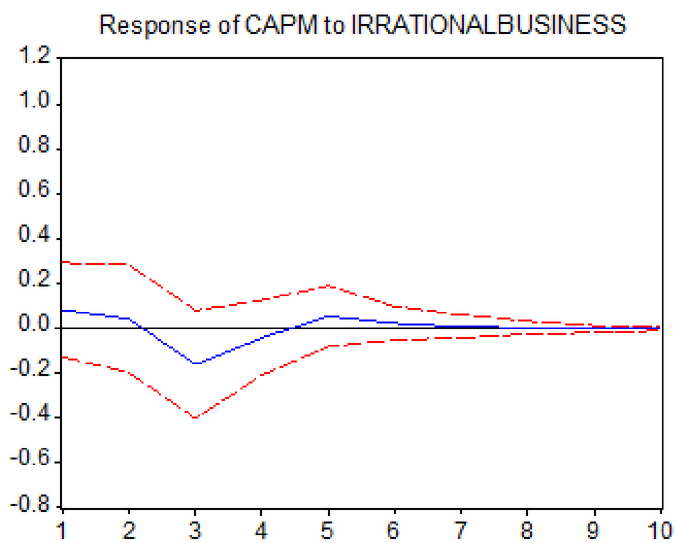


The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant. On each graph, "percentage returns" are on the vertical and "horizon" is on the horizontal axis.

FIGURE 2.7
Response of the CAPM Returns to the (a) Rational and (b) Irrational Sentiments of Businesses
(a)



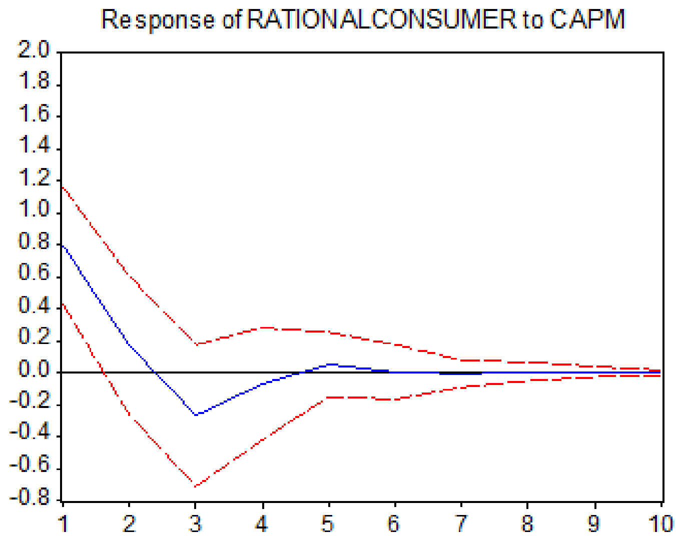
(b)



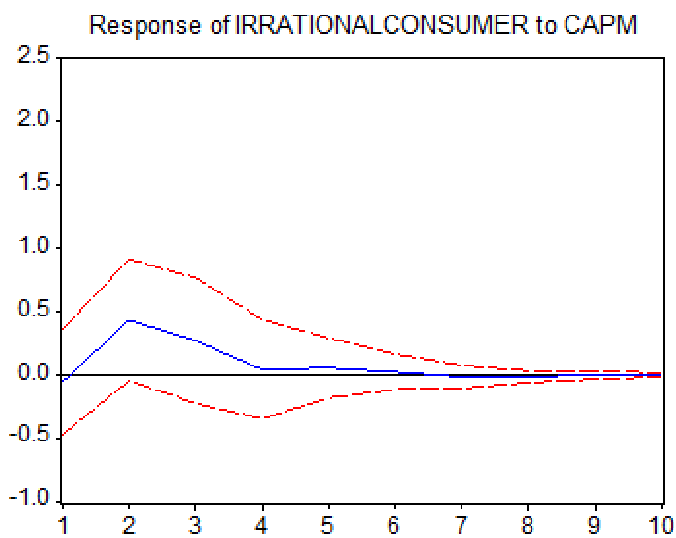
The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant. On each graph, "percentage returns" are on the vertical and "horizon" is on the horizontal axis.

FIGURE 2.8
Response of the (a) Rational and (b) Irrational Sentiments of Consumers to the CAPM Returns

(a)



(b)

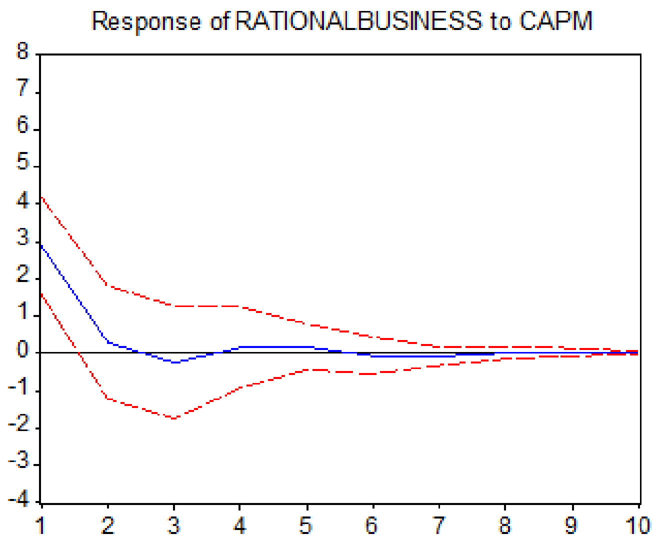


The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant. On each graph, “percentage returns” are on the vertical and “horizon” is on the horizontal axis.

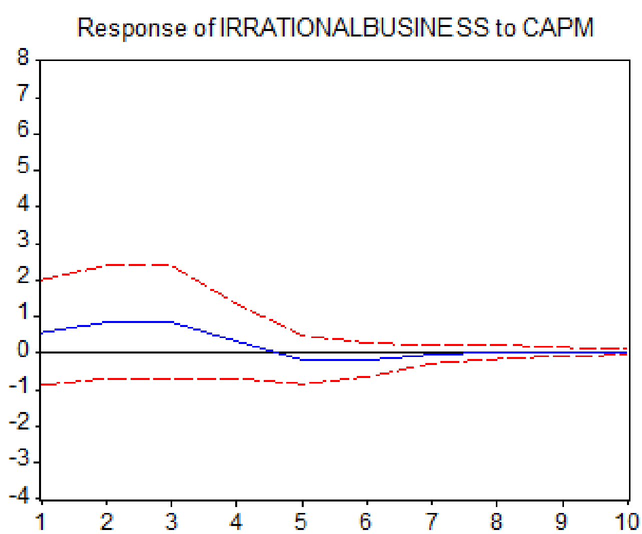
FIGURE 2.9

Response of the (a) Rational and (b) Irrational Sentiments of Businesses to the CAPM Returns

(a)



(b)



The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant. On each graph, "percentage returns" are on the vertical and "horizon" is on the horizontal axis.

3.8 Implications and Comparisons

There are implications of this study that might be of importance to individual and institutional investors, firms, creditors, governments, policy makers, and academic scholars.. The response of the ISE National-100 Index returns to a one time SD increase in the fundamentals driven (rational) component of sentiments is positive and significant for the first three months after the initial shock and becomes insignificant thereafter. However, the response of the same returns to a one time SD increase in the irrational component of sentiments is insignificant. Increases in the fundamentals driven component of sentiments indicate a good economic environment. This optimistic habitat is sourced from the actual improvements in the fundamental variables used in the study. It does intuitively make sense that stock returns are positively and significantly impacted by such optimistic environment. However, increases in the irrational component of sentiments do not cause any significant impact on the stock returns in Turkey. There may be two potential reasons for this insignificant effect: (1) The effect of irrational component of sentiments is too small to be detected as significant, which show that the investors do not show much irrationality, or (2) the number of individual investors in this relatively small stock market is too few compared to developed stock markets and therefore, the effect of the irrational sentiments on stock returns is wiped away easily and remains undetected. As it is indicated in the literature review section, individual investors are more prone to show exuberance compared to institutional investors and it is documented that the ISE has more institutional investors than individual investors. Such institutional investors are known to utilize more technical and fundamental analysis than individual investors (Gompers and Metrick, 2001).

The response of the fundamentals driven (rational) component of sentiments to a one time SD increase in the ISE National-100 Index returns is positive and significant for the first two months and insignificant thereafter. On the other hand, the response of the irrational component of sentiments to a one time SD increase in the returns is insignificant at all times. This result confirms that increases in the ISE National-100 Index returns also create an optimistic environment for the market participants and affect the fundamental variables positively. The strong bidirectional causality between the ISE National-100 Index returns and the fundamentals driven (rational) component of sentiments is verified with this study. Previous literature's assumption of unidirectional causality between stock returns and sentiment is insufficient and inaccurate.

Another important implication is that the effect of the fundamentals driven (rational) component of sentiments on stock returns is greater than the effect of the irrational component of sentiments in Turkey. This result is in line with previous studies of Verma et al. (2008) and Calafiore et al. (2009). The noise traders do not have enough power to influence the stock prices with their unpredictable sentiment changes in Turkey. Thus, the rational expectations theory of stock prices may be a valid argument in determining stock prices of the Istanbul Stock Exchange (Muth, 1961).

The analysis of the same relationships with the CAPM fitted excess returns reveals the same results. The CAPM fitted excess returns of the ISE National-100 Index subtract the estimated risk-free rate from the continuously compounded returns. Thus, only the risky parts of the returns are considered in the CAPM for both, the ISE National-100 Index returns and the ISE All Shares Index returns. The response of the excess returns on the ISE National-100 Index, or equity risk premium, to a one time SD increase in the fundamentals driven component of sentiments is positive and significant for the first three months. The response of the CAPM fitted excess returns to a one-time SD increase in the irrational component of sentiments is insignificant at all times. Moreover, the response of the rational component of the sentiments to a one-time SD increase in the CAPM fitted excess returns is positive and significant for the first two months but the response of the irrational component of the sentiments to a one-time SD increase is insignificant at all times. Such robust results confirm that the VAR model in this study captures the postulated relationships well.

This is the first study that investigates the relationship between the stock returns and the investor sentiment for a second generation emerging market. The results are completely consistent with the findings of Calafiore et al. (2009) and partly consistent with Verma et al. (2008). The studies by Calafiore et al. (2009) and Verma et al. (2008) focus on Brazil and United States, respectively. It can be concluded that the first generation emerging markets and the second generation emerging markets show similarities in their stock return responses to changes in sentiments and vice versa. The fundamentals driven component of sentiments and the stock returns have significant effects on each other whereas the irrationality driven component of sentiments and the stock returns have no significant impact on each other. The implication of such results is that emerging stock markets support the rational expectations of stock return argument. On the other hand, the effect of the irrational component of sentiments on the stock returns is significant in developed stock markets, which supports the noise traders' model argument. Utilizing the analysis based on the fundamentals variables used in the study may be beneficial and practical in determining the future stock market responses in the emerging markets. Individual and institutional investors, firms, governments, creditors, policy makers and academic scholars may use these fundamentals analysis in their decision making processes.

3.9 Conclusion, Limitations and Future Research

The purpose of this study is to examine the relative effects of fundamentals driven (rational) and irrational components of consumer and business sentiments on the ISE National-100 Index returns of Turkey. Previous literature prior to Verma et al. (2008) tends to classify investor sentiment as a complete irrational term which cannot be predicted using risk factors. However, it is a recent argument that consumer and business sentiments may be driven by both, fundamentals driven (rational) and irrational factors in Turkey. In general, a five variable VAR model is run and the following results are found: First, the impact of rational sentiments both at the consumer and business levels are greater than irrational sentiments on stock market returns in Turkey. Second, the immediate responses of the Istanbul Stock Exchange Index returns to sudden increases in the fundamentals driven component of sentiments are positive and significant for the first three months and there are significant effects of past performance on rational sentiments. In summary, significant bidirectional relationship between stock returns and rational component of consumer and business sentiments is confirmed. Lastly, the impact of irrational sentiments on ISE National-100 Index returns is insignificant both at the consumer and business levels. Contrary to the most previous studies and in line with Verma et al. (2008) and Calafiore et al. (2009), the results of this study supports that consumer and business sentiments are driven by both rational (fundamentals-driven) and irrational factors with distinctive effects on the stock market returns in Turkey. However, similar to Calafiore et al.'s (2009) study in Brazil but different from Verma et al.'s (2008) study in U.S, the impact of the irrationality driven component of sentiments on stock market returns remains insignificant for Turkey. One reason for this different result may be due to the distinction between emerging stock markets and developed stock markets. Brazil and Turkey as two important emerging stock markets show very similar behavior in that irrational component of sentiments reveals insignificant effects on the stock market returns. Emerging stock markets are usually dominated more by institutional investors rather than individual or consumer level investors. The lack of consumer or individual investor may be the reason why the impact of irrational component of sentiments is insignificant in these markets for now. As these markets develop more and the number of individual investors increases, we may be able to see significant effects of irrational component of sentiments in these markets.

One of the future extensions of this study may be inclusion of another widely asset pricing model, for example the Arbitrage Pricing Model (APT). Elton and Gruber (2010) argue that the APT model may present a more realistic picture in behavioral models as it assumes a marginal investor and it does not impose a rational investor assumption as CAPM does. Such critique on behavioral models in asset pricing is very recent and unexplored. Therefore, an application of a well-specified APT model may provide another means to check the robustness of the results and may reveal differing results and implications.

One of the limitations of this study is the risk-free rate in Turkey. The estimated risk-free rate may not be completely risk-free even though it is one of the widely used proxies in the literature as indicated in section 3.7.[8] One implication of this could be that the fundamental variables may also be predictors of the estimated risk-free rate. Inspired from this idea, another OLS regression model is run where the estimated risk-free rate (Rf) is the dependent variable and the fundamental variables used in the study are the explanatory variables. The results of this regression show that the inflation rate is a strong and significant predictor of the estimated risk free rate. Currency and terms of trade for Turkey are also significant variables at 5% level, in

[8] This proxy is used by Gursoy and Rejepova (2007) and it is estimated by using the Fisher's equation (Fisher, 1930).

predicting the estimated risk-free rate.[9] Fortunately, subtracting the estimated risk free rate from the rate of return on ISE National-100 Index and the rate of return on the market portfolio during the CAPM estimation eliminates the possibility of an interaction between the CAPM fitted excess returns and the rational components of sentiments during the VAR analysis. Therefore, no compromise is made during the interpretations of the VAR results. However, a future perfection for the risk free rate in this study may be possible if the Turkish Government issues a security with a 30-day maturity.

The results have important practical implications for investors and policymakers. Since they point out a relationship between sentiments and stock returns, it is obvious that sentiments do have pricing power in the stock prices of Istanbul Stock Exchange. Thus, the rational expectations theory of stock returns is found to be a valid argument in Turkey under such evidence. Moreover, the insignificant effect of the irrationality driven component of sentiments on stock returns reduces the possibility of underreaction and overreaction happening in the market. Consequently, reduced possibility of stock price distortion brings the stock prices to their intrinsic values. Overall, when the intrinsic values of the stocks are accomplished, the systematic risk of the Istanbul Stock Exchange may reduce. Decreased systematic risk in an emerging stock market like the Istanbul Stock Exchange may make the market more attractive to participants, which may also contribute the further development of efficiency in the market.

[9] The OLS regression results can be viewed in the Appendix B. 4.

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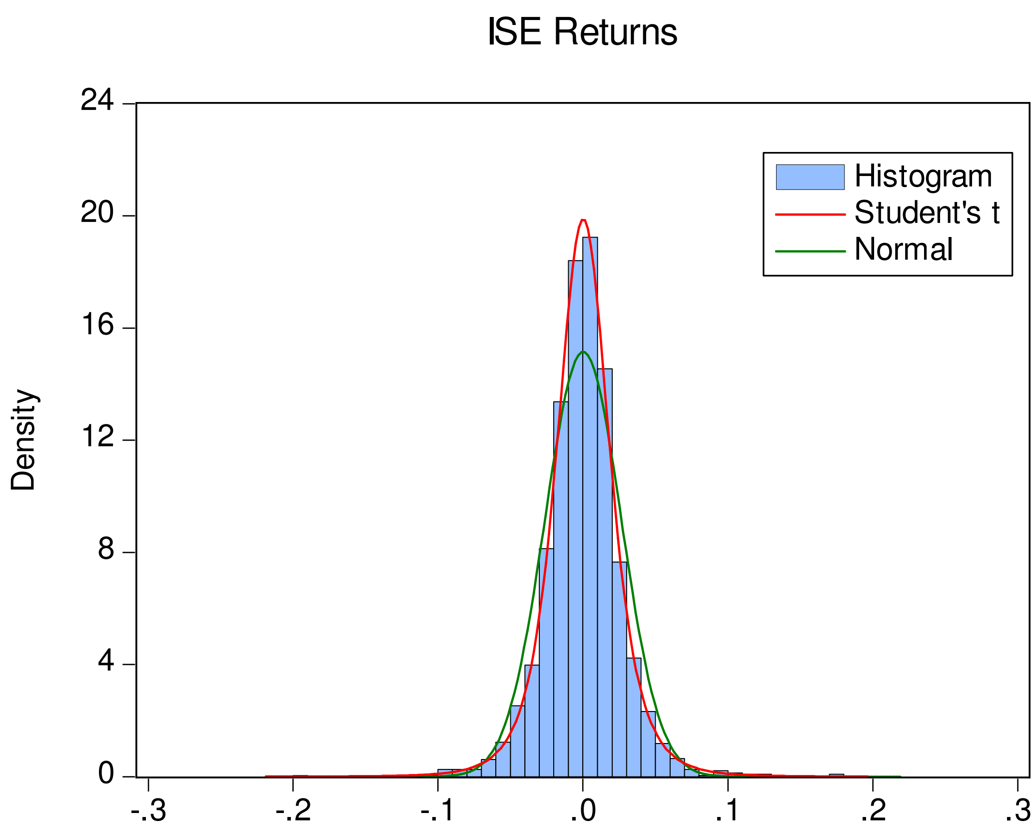
APPENDIX A

APPENDIX A.1

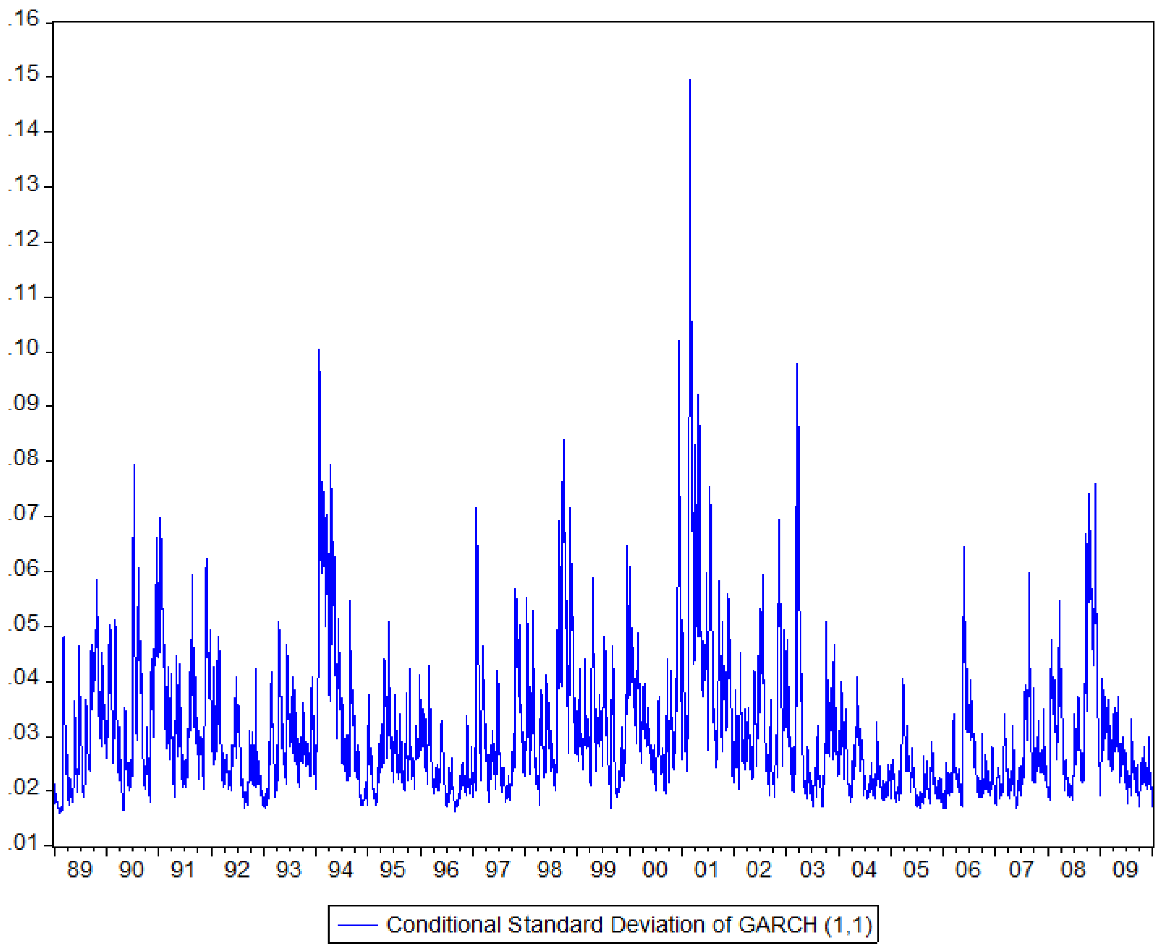
DISTRIBUTION OF THE ISE NATIONAL-100 INDEX RETURNS



APPENDIX A.2

CONDITIONAL STANDARD DEVIATION GRAPH OF THE GARCH (1,1) MODEL

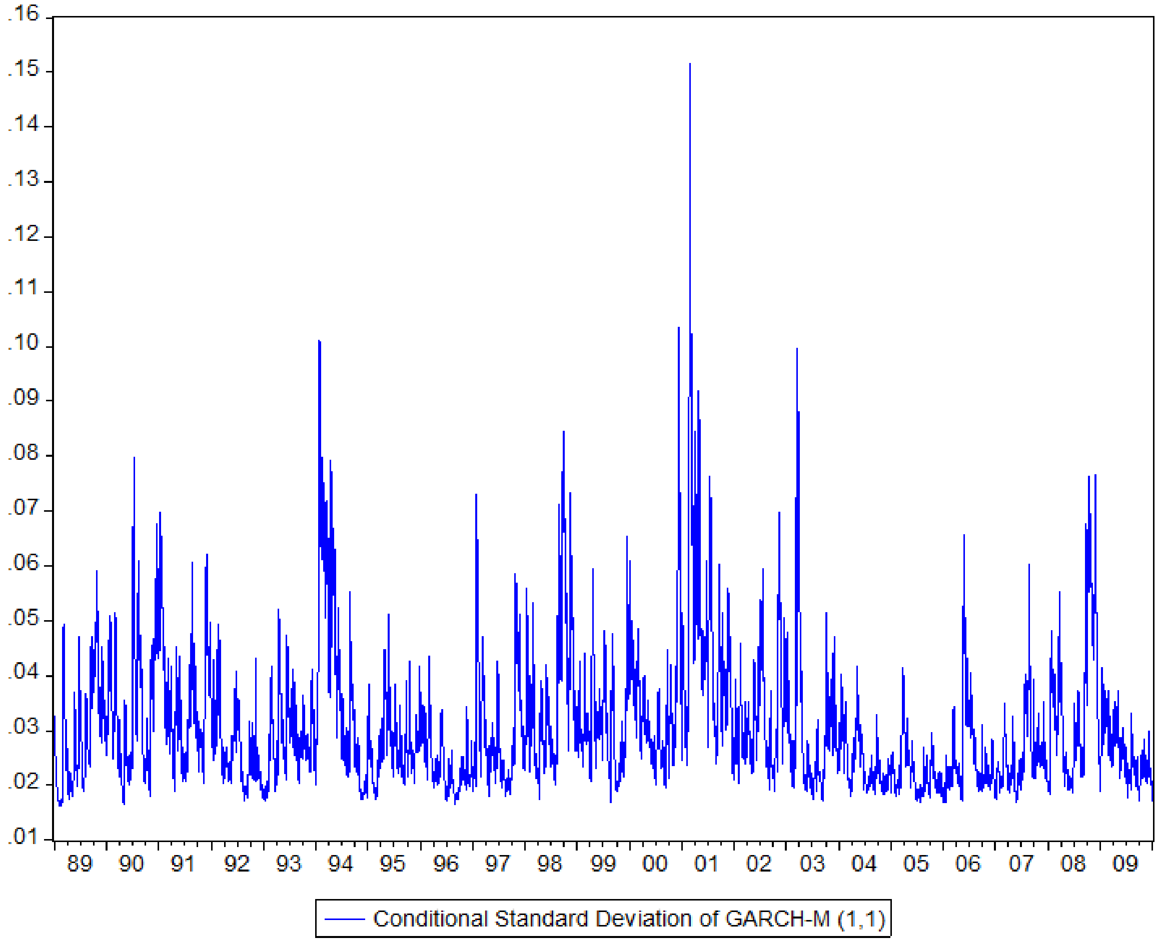
FULL SAMPLE WITH STUDENT'S T ASSUMPTION



APPENDIX A.3

CONDITIONAL STANDARD DEVIATION GRAPH OF THE GARCH-M (1,1) MODEL

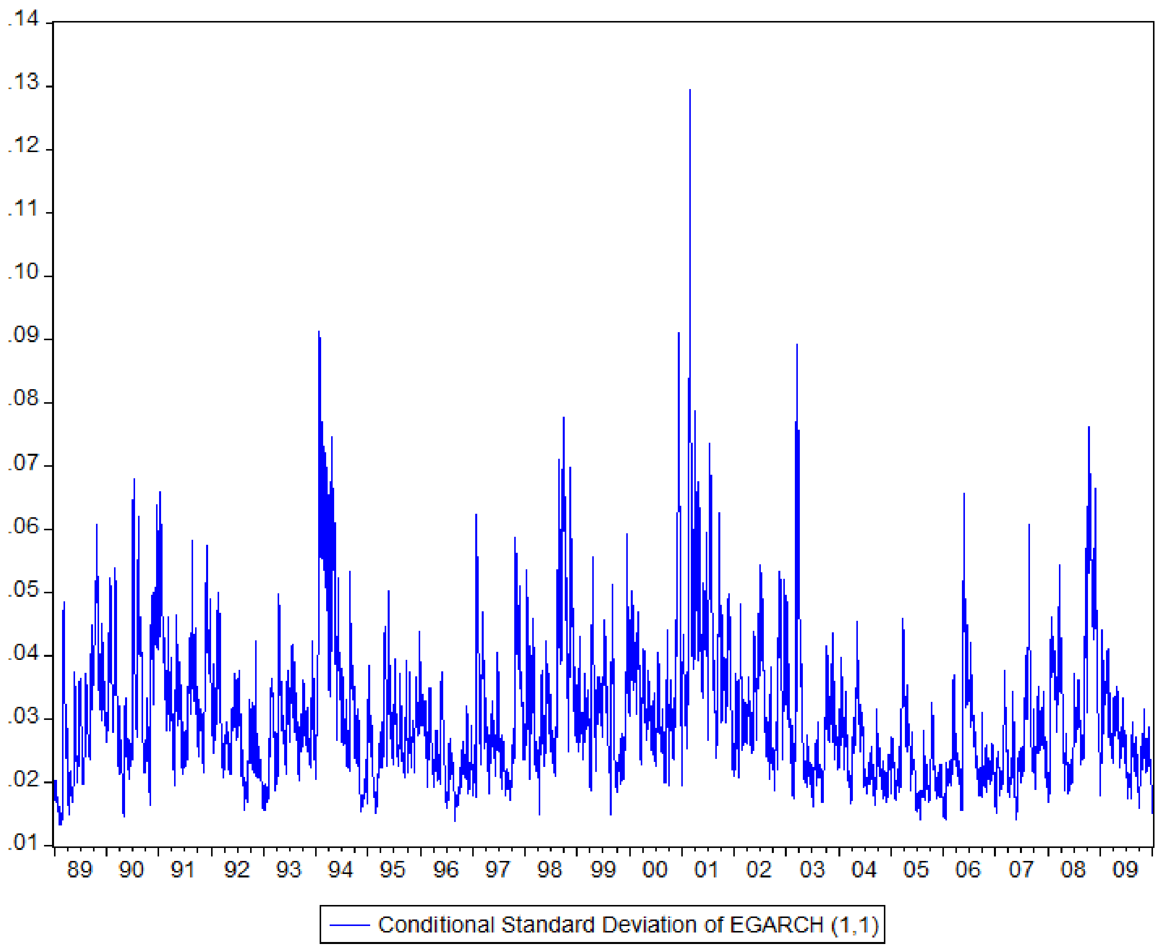
FULL SAMPLE WITH STUDENT'S T ASSUMPTION



APPENDIX A.4

CONDITIONAL STANDARD DEVIATION GRAPH OF THE EGARCH (1,1) MODEL

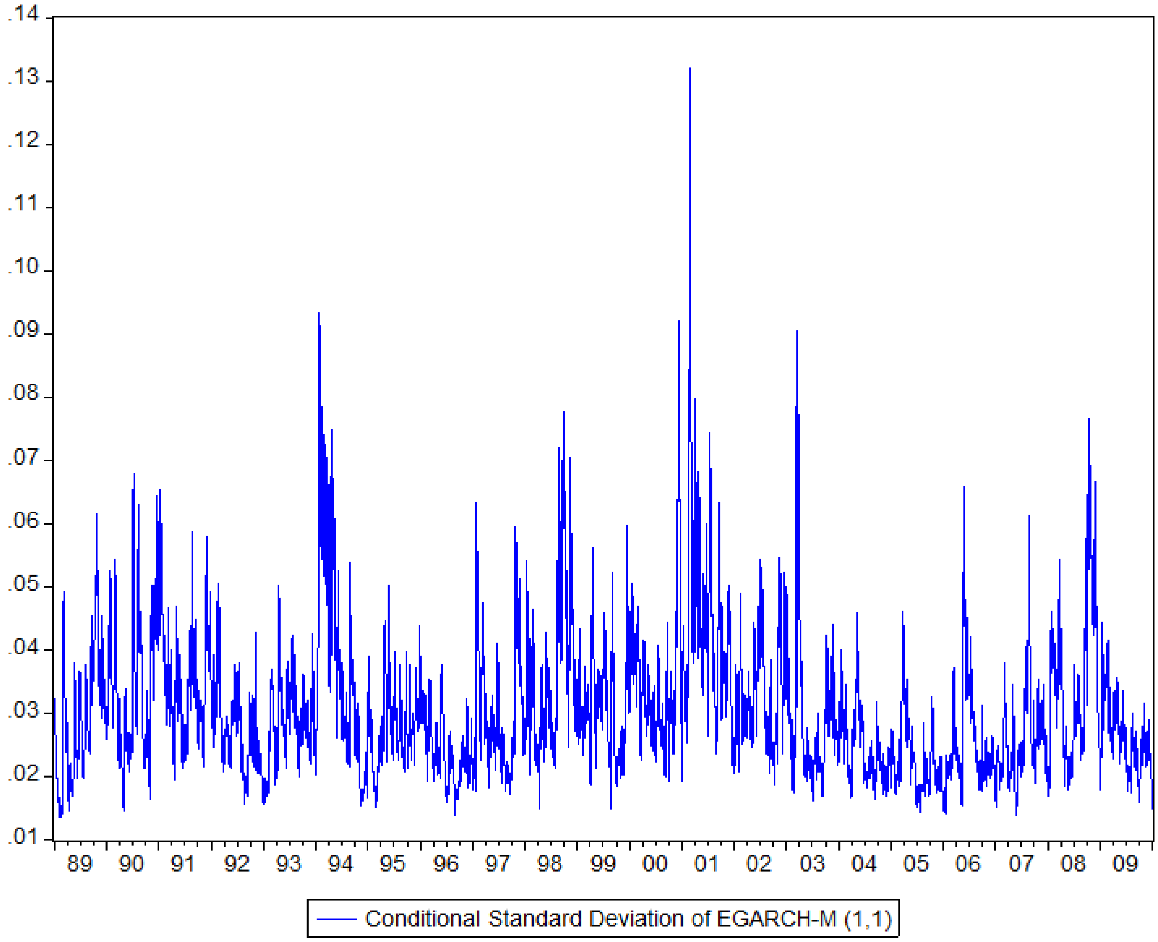
FULL SAMPLE WITH STUDENT'S T ASSUMPTION



APPENDIX A.5

CONDITIONAL STANDARD DEVIATION GRAPH OF THE EGARCH-M (1,1) MODEL

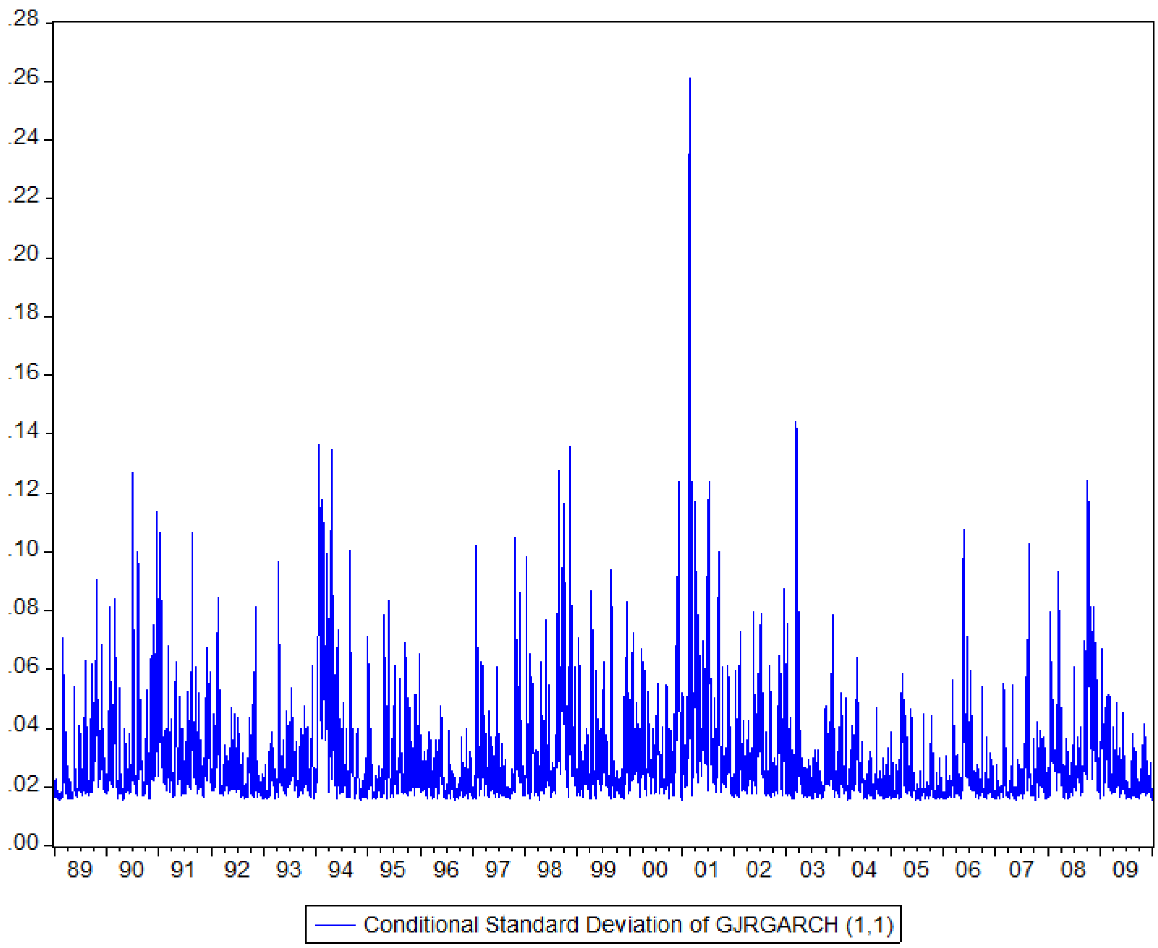
FULL SAMPLE WITH STUDENT'S T ASSUMPTION



APPENDIX A.6

CONDITIONAL STANDARD DEVIATION GRAPH OF THE GJRGARCH (1,1) MODEL

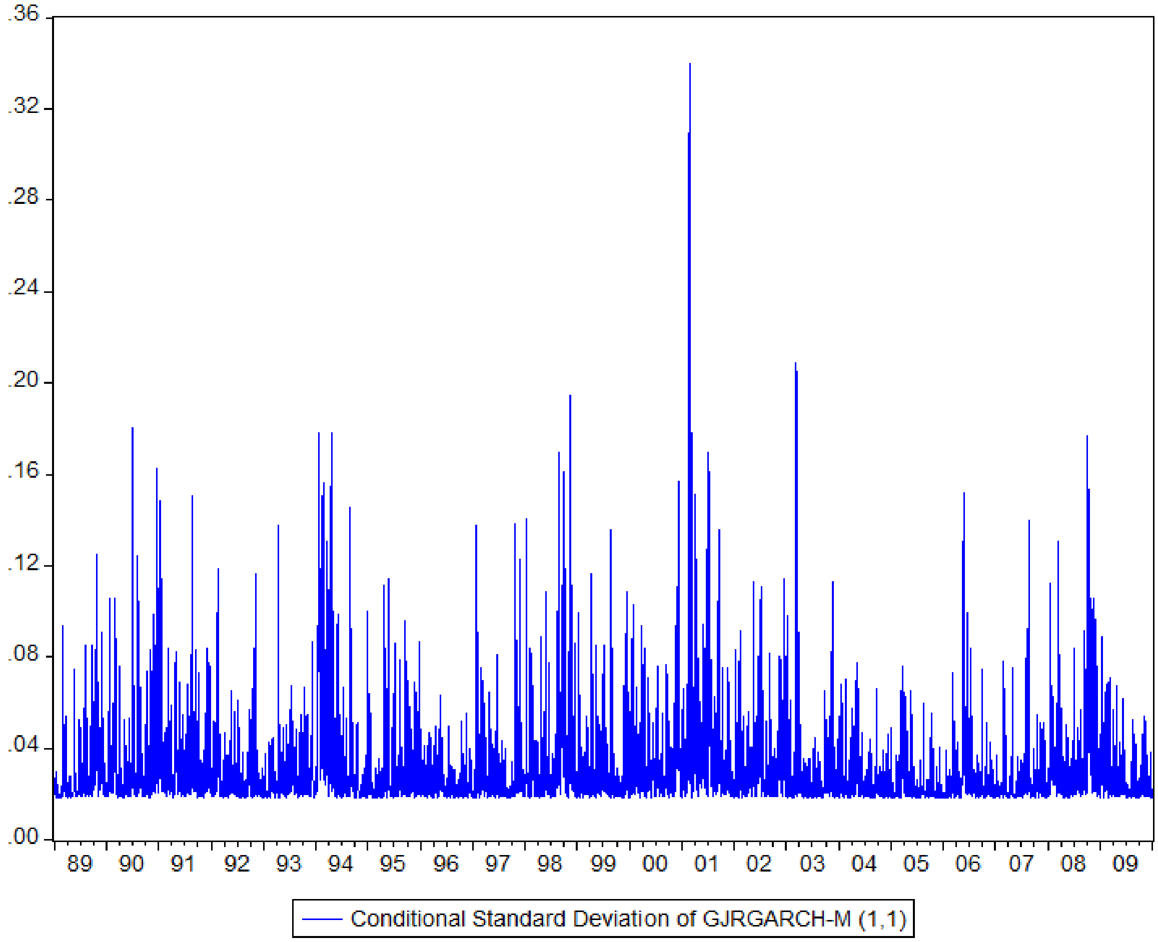
FULL SAMPLE WITH STUDENT'S T ASSUMPTION



APPENDIX A.7

CONDITIONAL STANDARD DEVIATION GRAPH OF THE GJRGARCH-M (1,1) MODEL

FULL SAMPLE WITH STUDENT'S T ASSUMPTION



APPENDIX B

APPENDIX B.1

VAR ESTIMATES WITH CONTINOUSLY COMPOUNDED RETURN (ISE100) SERIES

	ISE100	RATIONALCONSUMER	RATIONALBUSINESS	IRRATIONAL CONSUMER	IRRATIONAL BUSINESS
ISE100(-1)	-0.137527	-1.828071	-8.563085	-0.493952	-11.38865
	(0.15271)	(2.13259)	(7.52151)	(2.32308)	(8.15167)
ISE100(-2)	-0.004773	-4.105525	-16.09299	3.078964	7.249510
	(0.14235)	(1.98803)	(7.01166)	(2.16561)	(7.59911)
RATIONALCONSUMER(-1)	0.032706	0.265301	1.170071	0.223375	-0.824379
	(0.01430)	(0.19972)	(0.70439)	(0.21756)	(0.76340)
RATIONALCONSUMER(-2)	-0.005099	0.021149	0.441740	-0.345526	0.153460
	(0.01441)	(0.20129)	(0.70993)	(0.21927)	(0.76941)
RATIONALBUSINESS(-1)	0.001791	0.039729	-0.059329	0.048169	0.545639
	(0.00435)	(0.06079)	(0.21441)	(0.06622)	(0.23237)
RATIONALBUSINESS(-2)	0.001930	-0.009297	-0.088691	0.032780	-0.111559
	(0.00413)	(0.05769)	(0.20349)	(0.06285)	(0.22053)
IRRATIONALCONSUMER(-1)	-0.000681	-0.114679	-0.301139	0.293650	0.408987
	(0.00912)	(0.12733)	(0.44910)	(0.13871)	(0.48673)
IRRATIONALCONSUMER(-2)	0.010200	0.208670	0.591483	-0.026000	-0.237390
	(0.00849)	(0.11857)	(0.41819)	(0.12916)	(0.45323)
IRRATIONALBUSINESS(-1)	-0.000834	0.030695	0.201838	0.081242	0.085628
	(0.00257)	(0.03589)	(0.12657)	(0.03909)	(0.13717)
IRRATIONALBUSINESS(-2)	0.001148	-0.054051	-0.004676	-0.015753	-0.253745
	(0.00275)	(0.03841)	(0.13549)	(0.04185)	(0.14684)
C	0.028964	-0.256873	0.411743	-0.049019	0.298172
	(0.01605)	(0.22414)	(0.79054)	(0.24417)	(0.85677)
R-squared	0.251420	0.249076	0.202906	0.291009	0.129899
Adj. R-squared	0.122354	0.119606	0.065476	0.168769	-0.020119
Sum sq. residuals	0.731456	142.6555	1774.538	169.2796	2084.341
Log likelihood	58.95867	-122.9650	-209.9348	-128.8686	-215.4863
Akaike AIC	-1.390106	3.883044	6.403906	4.054163	6.564819
Schwarz SC	-1.033945	4.239206	6.760068	4.410325	6.920981

APPENDIX B.2

DESCRIPTIVE STATISTICS FOR THE ESTIMATED RISK FREE RATE (RF*) AND INFLATION RATE (INFTR) SERIES IN TURKEY

	RF*	INFTR
Mean	0.508949	0.695499
Median	0.386949	0.641381
Maximum	3.447157	2.600822
Minimum	-1.291705	-0.730188
Std. Dev.	0.865554	0.719166
Skewness	0.626780	0.396008
Kurtosis	3.952139	2.931644
Jarque-Berra	7.330695	1.869551
Probability	0.025595	0.392674

APPENDIX B.3

OLS REGRESSION RESULTS FOR THE CAPITAL ASSET PRICING MODELS

Dependent Variable: ISE100-RF*=CAPM1
Method: Least Squares
(ISE100-RF*)=C(1)+C(2)*(RM-RF*)

	Coeff.	Std. Error	t-Statistic	Prob.
C(1)	-0.003818	0.004881	-0.782240	0.4367
C(2)	0.993314	0.004754	208.9372	0.0000

R-squared	0.998422	Mean dependent var	-0.494270
Adjusted R-squared	0.998399	S.D. dependent var	0.901286
S.E. of regression	0.036062	Akaike info criterion	-3.779375
Sum squared resid	0.089734	Schwarz criterion	-3.715638
Log likelihood	136.1678	Durbin-Watson stat	2.846112

Dependent Variable: ISE100-RF*=CAPM2
Method: Least Squares
(ISE100-RF*)=C(2)*(RM-RF*)

	Coeff.	Std. Error	t-Statistic	Prob.
C(2)	0.995102	0.004157	239.3943	0.0000

R-squared	0.998408	Mean dependent var	-0.494270
Adjusted R-squared	0.998408	S.D. dependent var	0.901286
S.E. of regression	0.035962	Akaike info criterion	-3.798715
Sum squared resid	0.090529	Schwarz criterion	-3.766847
Log likelihood	135.8544	Durbin-Watson stat	2.840250

APPENDIX B.4

OLS REGRESSION RESULTS OF THE ESTIMATED RISK FREE RATE

Dependent Variable: RF*				
Method: Least Squares				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
BUSCON	0.018921	0.016584	1.140948	0.2582
COMPANY	3.96E-05	0.000175	0.225949	0.8220
COUNTRISK	0.000503	0.001679	0.299500	0.7655
ECONRISKPRE	0.149106	0.147401	1.011566	0.3156
EXCHANGE	1.011327	0.397314	2.545411	0.0134**
GROWTH	-0.003586	0.006223	-0.576256	0.5665
INFTR	1.051477	0.069807	15.06254	0.0000***
TOT	-0.021815	0.009013	-2.420384	0.0184**
R-squared	0.813653	Mean dependent var		0.508949
Adjusted R-squared	0.792947	S.D. dependent var		0.865554
S.E. of regression	0.393853	Akaike info criterion		1.080130
Sum squared residuals	9.772583	Schwarz criterion		1.335080
Log likelihood	-30.34462	Durbin-Watson stat		1.284164

***, ** Denotes significance at the 1% and 5% levels, respectively.

APPENDIX B.5
VAR ESTIMATES WITH CAPM FITTED EXCESS RETURN (CAPM) SERIES

	CAPM	RATIONALCONSUMER	RATIONALBUSINESS	IRRATIONAL CONSUMER	IRRATIONAL BUSINESS
CAPM(-1)	0.282894	-0.242823	-0.799687	0.199659	0.402521
	(0.14711)	(0.27313)	(0.97547)	(0.29106)	(1.01630)
CAPM(-2)	-0.198210	-0.031550	0.597858	0.135481	1.387494
	(0.15090)	(0.28015)	(1.00055)	(0.29854)	(1.04243)
RATIONALCONSUMER(-1)	0.019661	0.229518	1.014152	0.231812	-0.857093
	(0.11305)	(0.20989)	(0.74960)	(0.22366)	(0.78098)
RATIONALCONSUMER(-2)	0.023335	-0.090669	-0.199765	-0.324762	-0.242369
	(0.11153)	(0.20708)	(0.73955)	(0.22066)	(0.77051)
RATIONALBUSINESS(-1)	0.022886	0.059685	0.011936	0.019251	0.409817
	(0.03194)	(0.05931)	(0.21181)	(0.06320)	(0.22068)
RATIONALBUSINESS(-2)	-0.009036	-0.030937	-0.190946	0.045155	-0.111159
	(0.03158)	(0.05863)	(0.20941)	(0.06248)	(0.21817)
IRRATIONALCONSUMER(-1)	-0.056956	-0.114862	-0.316117	0.276830	0.271841
	(0.06991)	(0.12980)	(0.46357)	(0.13832)	(0.48298)
IRRATIONALCONSUMER(-2)	0.083793	0.134998	0.314641	0.022556	-0.158636
	(0.06426)	(0.11930)	(0.42607)	(0.12713)	(0.44390)
IRRATIONALBUSINESS(-1)	0.009946	0.042232	0.231118	0.067822	0.024280
	(0.02000)	(0.03713)	(0.13261)	(0.03957)	(0.13816)
IRRATIONALBUSINESS(-2)	-0.034890	-0.057904	-0.027198	-0.007654	-0.214538
	(0.02087)	(0.03875)	(0.13839)	(0.04129)	(0.14418)
C	-0.423246	-0.538384	-0.400333	0.155258	0.854994
	(0.13283)	(0.24662)	(0.88077)	(0.26280)	(0.91764)
R-squared	0.219715	0.199467	0.128687	0.276709	0.121036
Adj. R-squared	0.085183	0.061444	-0.021540	0.152004	-0.030510
Sum sq. residuals	44.11940	152.0799	1939.768	172.6938	2105.573
Log likelihood	-82.47812	-125.1721	-213.0063	-129.5575	-215.8359
Akaike AIC	2.709511	3.947017	6.492935	4.074131	6.574954
Schwarz SC	3.065673	4.303179	6.849097	4.430293	6.931116

APPENDIX B.6

OLS REGRESSION RESULTS OF IRRATIONAL CONSUMER AND BUSINESS SENTIMENTS

Dependent Variable: IRRATIONALCONSUMER
Method: Least Squares
IRRATIONALCONSUMER=C(1)+C(2)*(RM-RF)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.020973	0.253109	0.082860	0.9342
C(2)	0.069603	0.246516	0.282347	0.7785

R-squared	0.001154	Mean dependent var	-0.013394
Adjusted R-squared	-0.013322	S.D. dependent var	1.857606
S.E. of regression	1.869939	Akaike info criterion	4.117453
Sum squared residuals	241.2703	Schwarz criterion	4.181190
Log likelihood	-144.1696	Durbin-Watson stat	1.346323

Dependent Variable: IRRATIONALBUSINESS
Method: Least Squares
IRRATIONALBUSINESS=C(1)+C(2)*(RM-RF)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.632925	0.793415	0.797723	0.4278
C(2)	0.855226	0.772748	1.106733	0.2723

R-squared	0.017442	Mean dependent var	0.210655
Adjusted R-squared	0.003202	S.D. dependent var	5.871061
S.E. of regression	5.861654	Akaike info criterion	6.402506
Sum squared residuals	2370.771	Schwarz criterion	6.466243
Log likelihood	-225.2889	Durbin-Watson stat	1.887302

BIOGRAPHICAL SKETCH

Sidika Gulfem Bayram received a Bachelor's in Science degree in Business Administration from the Faculty of Political Sciences at Ankara University, Turkey in 1999. Upon completion of her undergraduate degree, she attended the University of Texas Pan American where she received her Master's in Business Administration in 2002. Ms. Bayram held several industrial positions at various companies including Wells Fargo Home Mortgage and Siemens Business Services. Prior to starting her PhD at the University of Texas Pan American in 2006, she taught college level accounting, general business, marketing and finance classes at the University of Texas Pan American and Yeditepe University in Istanbul, Turkey.

Ms. Bayram presented her research at major conferences in finance and accounting such as *American Economic Association Conference, Midwest Finance Association Conference, European Accounting Association Conference, and Society for the Study of the Emerging Markets Conference.* She also published her work in the proceedings of the *European Accounting Association, Southwest Decision Sciences, and Academy of Economics and Finance*. Her research interests include asset pricing and stock market volatility in emerging countries, behavioral finance, corporate finance, auditing and international financial reporting standards. Ms. Bayram earned her PhD degree in Business Administration with emphasis in Finance from the University of Texas Pan American in May, 2011.

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