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BEHAVIORAL FINANCE: OVERCONFIDENCE HYPOTHESIS AND EVIDENCES FROM ISTANBUL STOCK EXCHANGE

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DECLARATION

I hereby declare that this master's thesis titled as "**Behavioral Finance: Overconfidence Hypothesis and Evidences from Istanbul Stock Exchange**" has been written by myself without applying the help that can be contrary to academic rules and ethical conduct. I also declare that all materials benefited in this thesis consist of the mentioned resourses in the reference list. I verify all these with my honour.

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ÖZET

Yüksek Lisans Tezi

Davranışsal Finans: Aşırı Güven Hipotezi ve İstanbul Menkul Kıymetler Borsası'ndan Kanıtlar

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Etkin Piyasalar Hipotezi insanların tamamen mantıklı olduğunu varsayar. Oysa, gerçek dünyada yapılmış olan ampirik analizlerde bu varsayımla çelişen bulgular, anomaliler, tespit edilmiştir. Bu bulgulardan sonra, araştırmacılar alternatif açıklamalar aramaya başladılar ve böylece davranışsal finans olgusu gelişmeye başladı. Bu tez, davranışsal finansın bir alt konusu olan Aşırı Güven Hipotezini incelemek amacıyla hazırlanmıştır.

Bu tezde aşırı güven hipotezi iki test edilebilir hipotez yoluyla tasvir edilmiştir. İlk hipoteze göre, pazar kazançları yatırımcıların kendine duyduğu aşırı güveni arttırır ve bunun sonucunda yatırımcılar bir sonraki dönemde daha çok işlem yapar. İkinci hipoteze göre ise, aşırı güvenli yatırımcıların yarattığı aşırı işlem hacmi volatiliteyi arttırır. Ampirik analiz kısmında, Chuang ve Lee (2006)'nın kullandığı yöntemden yararlanılarak, Nisan 1991-Ocak 2011 tarihleri arasında İMKB'de aşırı güven hipotezinin varlığı test edilmiştir. Araştırma bulgularında aşırı güven hipotezinin öngördüğü üzere, getiriden işlem hacmine doğru bir pozitif nedensellik bulunmuştur. Ancak, şartlı volatilitenin aşırı güvenden kaynaklanan işlem hacmiyle beraber artmadığı ortaya konmuştur. Bu nedenle araştırma sonucu aşırı güven hipotezi ile uyumlu bulunmamaktadır. Bu tezin daha önce benzer çalışmalarda kullanılmamış olan

IMKB-100 endeksini kullanarak, Türkiye'deki aşırı güven hipoteziyle ilgili literatüre katkıda bulunacağı düşünülmektedir.

Anahtar Kelimeler: 1) Davranışsal Finans, 2) Aşırıgüven Hipotezi, 3) Etkin Piyasalar Hipotezi, 4) Piyasa Anomalileri, 5) IMKB

ABSTRACT

Master's Thesis

Behavioral Finance: Overconfidence Hypothesis and Evidence from Istanbul Stock Exchange

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Efficient market hypothesis assumes that people are fully rational. However findings contradicting with this assumption, anomalies , are detected in real-world empirical studies. After these findings, researchers attempt to find alternative explanations and by this way behavioral finance is started to be developed. This thesis has been constructed to examine overconfidence hypothesis which is a sub-title of behavioral finance.

In this thesis, overconfidence hypothesis is characterized by following two testable hypotheses. Based on first hypothesis, market gains are expected to increase investors' overconfidence and as a result of this, investors trade more in subsequent period. Based on second hypothesis, excessive trading of overconfident investors contributes to volatility. In empirical analysis, existence of overconfidence hypothesis in ISE is tested by benefiting from the methodology used by Chuang and Lee (2006) for the period between April 1991 and Jan 2011. In the findings of research, a positive causality is found from return to trading volume as overconfidence hypothesis foresees. However, conditional volatility is not found as increasing with trading volume caused by overconfidence. Because of that reason, result of research is not found as consistent with overconfidence hypothesis. This thesis is considered as

contributing to literature of overconfidence hypothesis in Turkey by using ISE-100 index that has not been used in similar studies before.

Keywords: 1) Behavioral Finance, 2) Overconfidence Hypothesis, 3) Efficient Market Hypothesis, 4) Market Anomalies, 5) ISE

BEHAVIORAL FINANCE: OVERCONFIDENCE HYPOTHESIS AND EVIDENCES FROM ISTANBUL STOCK EXCHANGE

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ABBREVATIONS

AMEX	: American Stock Exchange
APT	: Arbitrage Pricing Theory
CAPM	: Capital Asset Pricing Model
CRSP	: Center For Research in Security Prices
EMH	: Efficient Market Hypothesis
E/P	: Earnings/Price
GARCH	: Generalized Autoregressive Conditional Heteroskedacity
ISE	: Istanbul Stock Exchange
IQ	: Intelligence Quotient
MA	: Moving Average
NASDAQ	: National Association of Securities Dealers Automated Quotations
NPV	: Net Present Value
NYSE	: New york Stock Exchange
P/E	: Price/ Earnings
S&P	: Standards & Poors
TL	: Turkish Lira
USD	: United States Dolar

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INTRODUCTION

In traditional finance theories, people are assumed to be always rational. These individuals, who are defined as homo economicus, are assumed to have enough ability and logic in order to make decisions which will optimize their utility function. Nonetheless, human nature has a more complex structure than traditional theories foresee. This phenomenon is widely investigated in the disciplines line sociology and psychology. Psychology asserts that behavior of individuals bases on cognitive processes. In this framework, a new phenomenon that is behavioral finance appears in the literature of finance. Behavioral finance asserts that investment decisions also bases on mentioned cognitive processes. According to behavioral finance models, investors are affected by cognitive biases and because of that reason markets could not be efficient. Supporters of behavioral finance assert that investors take into account not only risk and return concepts but also other variables like previous beliefs. Namely, process of decision-making is not a perfect process. Generally, investors tend to make investment decisions which provide them maximum satisfaction rather than maximum utility.

This thesis is about the one of the concept of the behavioral approach: overconfidence. It aims to contribute the literature of overconfidence hypothesis studies in Turkey by examining phenomenon on ISE-100 index. It consists of three parts. In the first chapter efficient market hypothesis, which is the alternative of behavioral finance, and anomalies, which are findings contradicting with efficient market hypothesis, will be examined. Noise concept that is perceived as a discussion regarding efficient market hypothesis is also included in this chapter.

In the second chapter, behavioral finance theory is examined in detail. Related theories which are expected utility theory and prospect theory, heuristics and cognitive biases are also included.

In the third and last chapter, overconfidence phenomenon is concentrated on. Empirical literature on overconfidence is examined. Then model framework that will be used is given. Empirical part consists of two sections. In the first one, relation of overconfidence with trading volume is investigated through econometric methods. In the second one, relation of overconfidence with volatility is investigated through econometric methods. At the end of econometric analysis, return is found to Granger Cause trading volume. It is proven that investors tend to make more trades after they obtain return from their investments, namely their self-confidence increases by the returns obtained. After then another suggestion of overconfidence hypothesis is tested. At the end E-GARCH Analysis, market volatility is not found to be caused by excessive trades of overconfident investors.

This thesis is essential since:

It provides a detailed literature on EMH and it gives behavioral finance phenomena in a comparative manner with EMH.

It gives concepts from not only outlook of finance but also psychology. In a way, it has a characteristic of transitivity in two disciplines.

Empirical work about overconfidence hypothesis is scarce not only in Turkey but also in world generally, due to lack of well-defined and testable implications.

CHAPTER ONE
GENERAL OUTLOOK TO EFFICIENT MARKET HYPOTHESIS

1.1. EFFICIENT MARKET HYPOTHESIS

In this chapter, development and literature on efficient market hypothesis will be presented. Types of efficiency, models that have importance in empirical literature will be mentioned briefly. In addition, evidences countering efficient market hypothesis and anomalies will be examined in an organized manner.

As Modern Portfolio Theory is started to be accepted beginning from 1960s, number of studies regarding factors affecting stock prices increase. Authors wondered if price changes are independent from each other. Namely, they investigate if price changes are random or not.

Fama defines an efficient market in his study that is conducted in 1970, as the one in which prices are always assumed to “fully reflect” available information. That definition is the main source of efficient market hypothesis.

As noted by Fama 1970, all empirical work on efficient markets can be considered within the context of the general expected return or “fair game” model. However, in the early literature discussions of the efficient markets model are phrased in terms of random walk model.

With reference of Fama, Samuelson and Mandelbrot are the first ones who rigorously studied the role of “fair game” expected return models in the theory of efficient markets and the relationship between these models and random walk model.

First test of random walk model is made by a French student, called Louis Bachelier in 1900. His “fundamental principle” for behavior of prices is that speculation should be a fair game; expected profits to speculator should be zero. (Fama, 1970: 389) According to Bachelier , market will not be in the expectation of a decrease or increase in the real price since it only deals with current real price in the case of ceteris paribus. He also mentions that random walk mechanism of stock prices has some mathematical characteristics. (Altun, 1992:3)

In 1953, Maurice Kendall presents a study to Royal Statistics Society in which he examines the behavior of weekly changes in nineteen indices of British industrial share prices and spot prices for commodities like cotton and wheat. As a result, he proves that price changes in those markets tend to change randomly. He also suggests that change in prices from one week to next is independent from the change that takes place between that week and the week after. (Kendall, 1953: 13) After then Roberts examines market efficiency under three forms in 1967 and Fama improves and explains those three forms in 1970. Nonetheless according to Döm (2003), fundamental principles of efficient market hypothesis base on Samuelson (1965). Samuelson mentions that if all market participants' information and expectations reflected in prices in an informationally efficient market, price changes could not be estimated.

"A market in which prices always fully reflect available information is called efficient." (Fama: 1970: 383) He focuses the necessity that new information has to be reflected in the stock prices immediately and accurately. Because only if new information is reflected in prices immediately and accurately, investors will not be able to get abnormal return. According to fair game model that is developed by Fama , expected value of abnormal return in an efficient market is zero.

Definition of Fama is criticized by many experts including Fama himself, because the words "fully reflect" and "available information" is not clear enough. Leroy (1976), who accepts prominence of Fama's study, also criticizes Fama by saying Fama's model is tautology. (Leroy, 1976: 139) Leroy criticizes Fama because of that sentence he uses in his study; "Based on the assumption that the conditions of market equilibrium can be stated in terms of expected returns." Leroy states that equations used by Fama could not possibly generate testable implications since there is no restriction on the data. Fama rejected Leroy's tautology criticism in his study conducted in 1976. However, he accepts that a model is needed to be found between future price, which is constituted based on present price and existing information, and density function. He also makes some modifications in the definition of efficiency in that study. He states that " In an efficient market true expected return on any security is equal to its equilibrium expected value, which is, of course, also the market's assessment of its expected value. In an inefficient market, on the other hand, true expected returns and equilibrium expected returns are not necessarily identical." (Fama, 1976: 144) In his next study, Fama (1991) information costs and trading costs, namely cost of getting prices to reflect information, is preconditioned to be zero in strong version of efficiency hypothesis. Moreover, he adds that prices reflect information up to point where profits by acting on information do not exceed marginal costs.

EMH bases on three arguments that base on weaker assumptions. (Shleifer, 2000: 2)

- Investors are rational and expected to value securities rationally.

Here rationality refers to;

- As new information reaches to economic actors, they adjust their expectations according to new information by using Bayes Law.
- They make optimum decisions based on those expectations to maximize their utility as it is foreseen by expected utility theory.

- Investors' trades are random and offset each other without affecting prices.
- Trades of irrational investors, who are irrational in similar ways, are met by rational arbitrageurs who eliminate irrational investors' influence on prices.

In the second assumption, lack of correlation between strategies of irrational investors is assumed. However, trading strategies of investors could also be correlated which damages efficiency of markets.

Altun (1992) , explains assumptions of EMH in another way. (Altun, 1992:8)

- There are large numbers of participants in the market and investors do not have power enough to affect market individually.
- Trading costs and cost of getting information are fairly low. Changes in political, economical and social structure are reflected in the market immediately.

- Liquidity in the market is fairly high. Since transaction costs are low, security prices will accommodate general changes easily.
- Markets have a developed institutional structure; and regulatory legislation makes markets to work steadily.

Market Efficiency term is generally used to mention pricing efficiency (informational efficiency). Nevertheless efficiency is separated into three classes in the finance literature which are pricing (informational) efficiency, functional efficiency, allocational efficiency. (Altun, 1992:6) In a market that has pricing efficiency, information about security valuation will be always reflected in prices and it will not be possible to get abnormal returns by strategies that are followed after risk adjustments are made. In another words, in a price efficient market, investment strategies for outperforming market-index will not get abnormal returns after adjusted for risk and transaction costs. (Fabozzi and Modigliani, 1992: 274) Allocational efficiency refers to allocation of scarce resources into most efficient areas. Transactional efficiency is related to transaction costs that buyers and sellers hold in the market. It involves making transactions in the market with minimum cost. (Güngör, 2003:110) However, generally informational efficiency is meant by the term “efficiency”.

According to EMH, market is always in equilibrium. When new information comes into being, it will be reflected into prices immediately. By this way equilibrium is never distorted. In efficient markets, no one could get abnormal returns. However on contrary to EMH, anomalies are observed even risk adjustment is made by pricing models. According to EMH, market is always in equilibrium which means;

i. Prices reflect all available information
ii. It is not possible for an investor to beat the market consistently and continuously. (Bostancı,2003:7)

In an efficient market, new information will be reflected in market prices due to competition between investors. Transaction cost is required to be zero and information is required to reach all investors without cost (it is a prerequisite), if all available information will be reflected in market prices.

Investors find intrinsic value of their stocks by calculating net present value of stocks. A discount rate is determined according to risk condition of future cash flows. In equilibrium, that intrinsic value equals to price of stock in the market. Market is extremely sensitive to news that could affect risk of market and it immediately reflects that news into prices. As a conclusion, prices of stocks cumulate all available information and reveals result by calculating NPV.

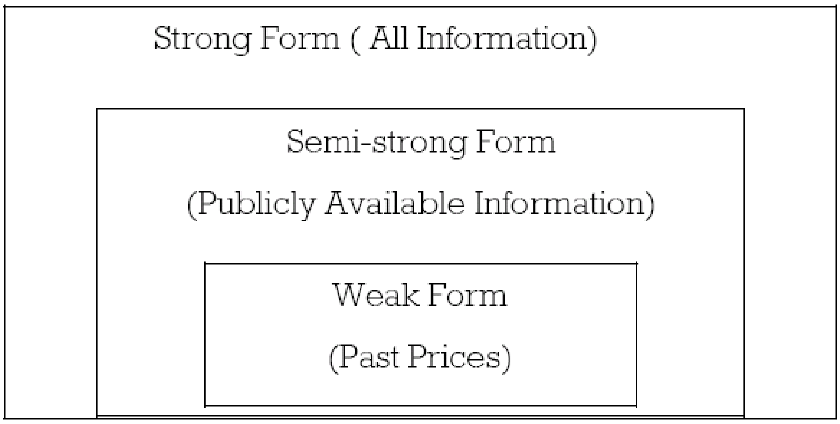
An efficient market refers to reflection of all available information in the market prices. However, Bostancı (2003) concludes that exogenous variables like changes in technology could increase or decrease prices. (Bostancı, 2003:7) If such a change occurs, equilibrium line of the stock will shift up or down. Efficient market hypothesis asserts that prices are not above or below from their intrinsic value, basically it assumes that market is in equilibrium.

Many researchers have studied upon efficiency of markets. Some found evidences supporting hypothesis, some find opposing evidences. A general error made in the test of efficiency is required to be explained. Authors suggesting efficiency of markets generally use randomness of prices as evidence. Nonetheless in efficient markets prices are determined randomly, whereas randomness of prices does not warrant efficiency of markets.

1.1.1. Types of Market Efficiency

Fama who studies market efficiency for the first time in 1965, delineates three levels of market efficiency. (Mandacı and Soydan, 2002: 135) Distinction between them bases on information that is taken into consideration in determination of security price. **Figure 1** exhibits three types of efficiency.

Figure 1. Types of Market Efficiency



(Jones, 2003: pp. 628.)

1.1.1.1. Weak-Form Efficiency

If current and past prices could not lead to make significant predictions about future price changes, market is said to be in weak-form efficiency. In weak-form efficiency stock prices already reflect past prices and trading history of security. In weak-form efficient markets, past stock price data are publicly-available and almost costless to obtain. (Bodie, Kane, Marcus, 2009:348) However by using those publicly available data, investors could not get abnormal returns. Investors, who select stocks based on price patterns or trading volume,- referred to technical analysts or chartists, do not do better than market. (Fabozzi and Modigliani,1992: 274) They might even do worse due to higher transaction costs related with frequent buying and selling of stocks.

1.1.1.2. Semi-Strong Form Efficiency

This version implies that price of security reflects all publicly available information. Such information contains in addition to past prices, fundamental data on firm’s product line, quality of management, balance sheet composition, patents held, earnings forecasts and accounting practices. (Bodie, Kane, Marcus, 2009: 349) Semi-strong form efficiency also includes weak form efficiency. This means in a market that is in semi-strong efficiency, it is impossible to make predictions about future prices by using past and publicly available prices. It is so because that information has been already reflected in prices. Moreover, in this form of efficiency investors could not get abnormal returns by using not only technical analysis but also fundamental analysis. However, insider traders still could get abnormal returns.

1.1.1.3. Strong Form Efficiency

"The strong form tests of the efficient markets model are concerned with whether all available information is fully reflected in prices in the sense that no individual has higher expected trading profits than others because he has monopolistic access to some information." (Fama, 1970: 409) In other words, strong form efficiency suggests that stock prices reflect all information about firm, even the one that is available to only for company insiders. Therefore, in that form of efficiency none of the analysis method will work to get abnormal return. However, even Fama himself, suggests that this model is not an exact description of reality. (Fama, 1969:409) It could even be qualified as extreme.

When all efficiency forms are taken into consideration, it will be seen that they are not independent. Namely, a semi-strong form efficient market also needs to be efficient in the weak form. Similarly, a strong form efficient market has to be efficient both in the weak form and in the semi-strong form.

Here it is necessary to explain two essential cases which have important roles in empirical literature. These are submartingale model and random walk model.

1.1.2. Submartingale Model

Fama (1970) states that price sequence P_{jt} for security j, follows a submartingale based on information set Φ_t . (Fama, 1970:386) This assumption is summarized as

$$\mathbf{E(P_{j,t+1})} \mid \Phi_t \geq \mathbf{P_{j,t}} \quad \text{or equivalently} \quad \mathbf{E(R_{j,t+1})} \mid \Phi_t \geq \mathbf{0} \quad \mathbf{(1)}$$

That statement also shows that expected value of subsequent period's price that is determined based on a specific information set will be equal to current price or higher than current price.

In the statement above, expected value of future returns conditional on Φ_t , could not be zero. This indicates that trading based on information set Φ_t , could not generate higher expected profits than it could be attained by simply buy and hold strategy. As a conclusion, submartingale model asserts that past price changes data is not useful for estimating future expected price changes.

1.1.3. Random Walk Model

Efficient Market Hypothesis asserts that successive price changes that reflect all available information set are independent and successive price changes (returns) are assumed to have identical distributions. (Fama, 1970:386) In other words, distribution of subsequent returns is said to be independent from current information set. These two hypotheses together constitute random walk model. We can perceive random walk model as a narrower version of efficient market hypothesis.

Proponents of random walk model supports that expected value of a stock could not be determined based on past price changes of stock. Furthermore they assert that future value of a stock will be independent from past price changes. That situation approaches random walk model to expressions of proponents of weak form efficiency. Nonetheless, two are separate things. If stock prices changes randomly parallel to random walk model, this means it is impossible to get abnormal return by using past price changes which validates efficiency in the weak form. Namely, efficiency of markets brings randomness of prices together. However, randomness of prices does not imply efficiency of markets. (Altun, 1992:16)

1.1.4. Evidences Countering Efficiency of Markets

Evidences countering efficiency of markets could be listed under five headlines:

1.1.4.1. High Trading Volume

If markets are constituted by rational investors as EMH asserts, since these investors will have homogenous expectations, only a few transactions are expected to be held. Mentioned a few transactions are made with liquidity and rebalancing needs. (Thaler, 1999b:14) Nonetheless this is not the case today. According to EMH, rational investors are expected to not to make transactions by basing on unannounced information. But today this is done frequently to get abnormal returns. In other words, in a market where everybody knows that all investors are rational if any shares are offered for sale, buyers have to wonder what information do sellers have that buyers themselves do not.

1.1.4.2. Equity Premium Puzzle

Traditional finance models assume that investors require a rate that is higher than risk free rate to invest in stock market. For instance, in CAPM model expected rate of return required is higher than risk free rate in the amount of risk premium which is a linear function of beta of stock. According to study prepared by Benartzi and Thaler (1995), annual returns of stocks and treasury bills are about 7 percent and less than 1 percent respectively. (Benartzi and Thaler, 1995:73) If this is the case, why don't investors invest all savings into stock market? Intuitive answer to this question is stocks are riskier than bonds. This could be logical if only short-term volatilities examined. (Bostancı, 2003:11) However, when long-term volatilities examined this would not be the case. That case which refers to tendency of investors to avoid holding stocks is called "equity premium puzzle" by Prescott and Mehra. Benartzi &Thaler (1995) try to explain equity premium puzzle by "myopic loss aversion". Loss aversion is used to explain tendency of decision makers to weigh losses more heavily than gains. Myopic adjective is added due to fact that even investors invested in long-term tend to care about short-term gain-loss situation. Benartzi and Thaler (1995) conclude that loss aversion explain much of equity premium puzzle. A more recent study, Shiller (1999) states that riskiness of stocks is not a justification of equity premium since most of the investors is long-term investors. Moreover, he asserts that long-term bonds, not the stocks that are riskier in real terms. He attributes that inference to high variability of consumer price index over long time intervals, despite its low variability from month to month. (Shiller, 1999:7)

1.1.4.3. Volatility

In a rational market, prices are expected to change only when new information arrives or there is a dividend expectation. Moreover, real stock prices are expected to be equal to net present value of optimally forecasted future real dividends. However from time on which Shiller's research was published in 1981, academicians realize that stock prices change more than justified by changes in intrinsic value which is measured via NPV of future dividends. For instance, Leroy and Porter (1981) state that stock prices seem more volatile than it is foreseen by efficient market hypothesis.

1.1.4.4. Predictability

Efficient market hypothesis suggests that future stock prices could not be predicted by using available information in the market. However, many deviations are observed indicating that future prices can be predicted by using measures as price to book ratios, company announcements of earnings, share repurchases, initial public offerings, size of companies. (Thaler, 1999b:14) For example, Campbell and Shiller (1988) find earnings-price ratio as a powerful predictor of stock return.

Banz (1981) and Reinganum (1981) find other anomaly "size effect" contradicting with market efficiency which refers to higher average stock returns of smaller firms compared to average stock returns of larger firms.

To sum up, all of the anomalies mentioned in the anomalies section serves as a tool for predicting future stock prices.

1.1.4.5. Dividends

Modigliani and Miller (1958) indicate that when there is no taxes, dividend policy is irrelevant in an efficient market. Nevertheless, Thaler (1999b) states that under tax system of USA, dividends are taxed at a higher rate than capital gains. As a result of that, in a rational world companies should prefer their taxpaying shareholders to repurchase shares instead of paying dividends. However, companies still pay cash dividends and stock prices rise when dividends paid. In a rational world, neither has a satisfactory explanation.

1.2. FINDINGS CONTRADICTING WITH EFFICIENT MARKET HYPOTHESIS: ANOMALIES

Efficient market hypothesis evolves from Eugene Fama's dissertation "The Behaviour of Stock Market Prices" in 1965. Based on that theory, an investor could only get higher returns only if he takes on more risk. Mentioned risk is the one that could not be diversified away. According to that hypothesis, it is not probable for market to be beaten. Investors are said to be always paying a "fair price". Unique thing investors have to consider is which risk-return trade off they want to be involved in. However, this hypothesis is not absolutely accurate.

Although Jensen (1978) mentions that there is no other proposition in economics that has more solid empirical evidence supporting it than EMH, it accepts that inconsistencies are begun to be detected as better data become available and as econometric sophistication increases. (Jensen, 1978:1) And after that explanation, authors start to investigate empirical findings that contradict with efficient market hypothesis. Those findings are said to be anomalies.

Today, anomalies pose a frequent research topic. Nevertheless, efficient market hypothesis is still a discussion subject. Because of the fact that there are findings both supporting efficient market hypothesis and opposing it; many authors and professionals approach EMH with skepticism while others investigating anomalies contradicting efficient market hypothesis. Warren Buffett who is the third wealthiest person as of 2010 is one of the professionals approaching it with skepticism. He explains his outlook regarding efficient markets as "I would be a bum in a street, with a tiny cup, if the markets were efficient." (Taşkın,2006 :26)

Frankfurter and Mcgoun (2001) include two definitions of the word "anomaly" in their study. The first one is from Oxford English Dictionary that is "unevenness, inequality, of condition, motion, etc". Second one is "irregularity, deviation from the common order, exceptional condition or circumstance." Use of word "anomaly" in finance is more relevant with the second definition.

Definition of anomaly is made by Keim as cross-sectional and time series patterns in security returns that are not predicted by a central paradigm or theory. (Keim, 1983:1) Thaler (1987) adds that an empirical result is anomalous if it is difficult to rationalize or if implausible assumptions are necessary to explain it within the paradigm.

Anomalies are results of weak form efficient tests, especially for developed markets. (Demireli, 2008:224) In that section anomalies observed in stock markets will be explained. As it could be seen from Table 1 anomalies will be examined as sectional anomalies, calendar (seasonal) anomalies, technical anomalies, pricing anomalies, political anomalies and economic anomalies. Calendar anomalies will be examined under headlines below:

i. **Daily Anomalies**
   - Day of the Week Effect/ Weekend Effect
   - Intraday Effect

ii. **Monthly Anomalies**
   - January Effect
   - Intra-month Effect
   - Turn-of-the Month Effect

iii. **Yearly Anomalies**
   - Turn-of-the Year Effect

iv. **Anomalies Related to Holidays**

Table 1. Types of Anomalies

Calendar Anomalies	Sectional Anomalies	Technical Anomalies	Pricing Anomalies
1.Daily Anomalies -Day of the Week Effect/ Weekend Effect - Intraday Effect **2.MonthlyAnomalies** -January Effect -Intra-month Effect -Turn-of-the Month Effect **3.Yearly Anomalies** -Turn-of- the Year Effect **4.Anomalies Related with Holidays**	**1.**Size Effect **2.** Book Value/ Market Value Effect **3.**Price/Earnings Ratio Anomaly **4.** Neglected Firm Effect	**1.**Moving Averages **2.**Support And Resistance	-Underreaction -Overreaction

1.2.1. Calendar Anomalies

Calendar anomalies address the deviations that are observed in stock returns based on time. These anomalies are observed systematically in specific days, weeks, years.

Even though these deviations could be an indicator of market inefficiency, this does not necessitate market inefficiency. (Schneeweis and Woolridge, 1979:939) Schneeweis and Woolridge suggest that seasonal return could also take place in an efficient market due to anticipated seasonal patterns embedded in underlying determinants. Those determinants could be counted as tax regulations, government monetary policy, seasonal information lags and risk adjustments.

According to EMH, stock returns are independent from time. In other words, time periods are indifferent in respect of returns. It points out that it is impossible to predict future returns and get abnormal returns by using observed return trend. Nonetheless, calendar anomalies contradict with that view. Many findings indicate that stock returns could be prescribed and in specific time periods more negative or more positive returns are acquired. Anomalies are observed not only in stock markets but also in gold, exchange, bonds and bills markets. (Barak, 2008:126)

1.2.1.1. Daily Anomalies

Day of the week effect is the most frequent subject of daily anomalies on which many articles written. Contrary to efficient market hypothesis, researches made show that average returns of different days of the week are not same. Moreover, statistically significant return differences are observed between days of the week. Aim of the investigators testing anomalies regarding days of the weeks is to examine if a specific day or days of the week provides higher or lower average returns than other days**.**

1.2.1.1.1. Day of The Week Effect

First study on day of the week effect is done by Cross (1973). He examines returns on Standard and Poors index of 500 stocks for the period 1953-1970. He finds negative returns for Mondays and positive returns for Fridays respectively by using 844 sets of Fridays and following Mondays. He concludes that S&P Composite index rises on 523 Fridays from 844 Fridays or in other words, it rises on 62 % of all Fridays. However, index rises on 333 Mondays from 844 Mondays. In other words, index rises on 39,5% of all Mondays. Fridays' mean return is determined as 0.12 % compared to -0,18 % mean return of Mondays.

French (1980) investigates day of the week effect by using return of S&P 500 index for the years 1953-1977. He finds negative returns for Mondays, whereas he finds positive returns for Fridays. According to "Calender Time Hypothesis" he dubbed prices should rise on Mondays relative to other days, since there are three calendar days from closing of Monday and closing of Friday rather than one calendar day. He also offers "Trading Time Hypothesis" stating returns are only generated during active trading. This means returns have to be same for each trading day. He states that Mondays have negative returns, however all other days have positive returns for each of five-year sub-periods. He also investigates if negative returns of Mondays are related with closed-market effect. Nevertheless, if this would be the case returns should be lower in the days following holidays. Instead he finds higher average returns than normal on the days following holidays.

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Theobald&Price (1984) examine day of the week effect for London Stock Exchange for the years 1975-1981 and document negative average returns for Mondays. This result is partially attributed to Settlement Date System employed on London Stock Exchange.

Jaffe&Westerfield (1985) investigate day of the week effect in the international markets of U.K, Japan, Canada and Australia by using daily data of stock market indexes. Foreign indexes and time periods are given as Japan-The Nikkei Dow Index 1970-1983, Canada- Toronto Stock Exchange Index 1976-1983, Australia-The Statex Actuaries Index 1973-1982, Financial Times Ordinary Share Index 1950-1983. In the study, authors confirm existence of day of the week effect. Authors also document that lowest average return is acquired on Tuesdays for Japan and Australia and on Mondays for U.K and Canada. Furthermore, no evidence is found showing either measurement error or settlement procedures cause seasonality in stock market returns. It is also investigated that if anomaly is caused by different time zones countries take place. However, time zone is said to be insufficient to explain Japanese seasonality and whereas it explains Australian seasonality partially.

Lakonishok and Maberly (1990) conclude that NYSE has a lower trading volume on Mondays than other days of the week despite tendency of individual investors to trade more on Mondays. Due to that reason, authors attribute low trading volume realized on Mondays to tendency of institutional investors to trade less. They also detect that individuals tend to increase number of sell transactions on Mondays.

Kato (1990) examines day of the week effect in Japanese stock returns by using value weighted index of Tokyo Stock Exchange. Low returns on Tuesdays and high returns on Wednesdays are observed. Furthermore, author mentions that low Tuesday returns may be attributed to Monday effect in the U.S due to the fact that

Tokyo Stock Exchange opens 14 hours before than NYSE. Japanese weekly pattern is said to be analogous to American pattern led by one day.

Aggrawal and Tandon (1994) look seasonal patterns in stock markets of eighteen countries that are Belgium, Denmark, France, Germany, Italy, Luxembourg, Netherlands, Sweden, Switzerland, UK, Hong Kong, Japan, Singapore, Brazil, Mexico, Canada, Australia, New Zealand for the period between December 1981 and January 1983. Authors observe daily seasonality in nearly all countries, weekend effect in only nine countries. They mention that returns tend to increase from beginning of the week to end of the week. Namely, on Mondays and Tuesdays indices are said to be decreasing, while on other three days it is increasing.

Balaban (1994) examines day of the week effect in ISE composite index return data for the period between January 1988 and August 1994. For that period although it is not significant, the lowest and negative average return is observed on Tuesdays. All of the average returns are negative except for the years 1989 and 1993. Highest significant return is observed on Friday at 1 % significance level. Moreover, Friday is the unique day on which all average returns are positive. Highest volatility is observed on Mondays for each year, whereas lowest volatility is obseved on Fridays.

Metin, Muradoğlu and Yazıcı (1997) study day of the week effect on ISE by using ISE-100 composite index for the period 4 January 1988-27 December 1996. They acquire a significant and strong Friday effect both in the base of TL and USD. They find a positive Monday effect in TL based calculations. Positive Monday effect is attributed to high inflation Turkish economy has faced for years. Because, inflation causes nominal returns to rise, however it causes real returns to follow a fluctuating way. A negative Monday effect is recorded but its coefficient is statistically insignificant.

Berument and Kıymaz (2001) examine day of the week effect in the framework of stock market volatility by using S&P 500 index for the period Jan1973-Oct 1977. They conclude that day of the week exists not only in volatility, but also in return equations. Highest return is realized on Wednesday, whereas lowest is realized on Monday. Moreover, highest volatility is realized on Friday and lowest is realized on Wednesday.

Berument et al (2004) examine day of the week effect on stock returns and volatility for ISE for the period 1986-2003 by using GARCH modeling. Days providing highest and lowest returns , are found as Friday and Monday respectively. Volatility is highest on Mondays and lowest on Fridays.

Atakan (2008) investigates the existence of day of the week effect between 1987 and 2008 by using ISE-100 index. She records higher returns on Fridays and lower returns on Mondays. Since day of the week effect is observed, author concludes that ISE is not efficient even in the weak form.

According to Atakan (2008), investors who purchase financial instruments by credit tend to make that transactions on Thursdays and Fridays to avoid interest payment of weekend. Since stocks that are bought by credit will appear on the account of the investor on Monday or Tuesday, investors will not pay credit interest for weekends. Such buy transactions could create higher average returns on Fridays. Atakan also suggests that firms tend to make positive announcements in the weekdays, whereas negative announcements are tended to be made on the weekends or on Fridays after the closing of stock market. They have such a tendency in order to prevent sell transactions that are made in panic. As a result of that tendency, author states that Mondays are riskier and have higher volatility than other days.

Kıyılar and Karakaş (2005) examine anomalies in ISE for the period between 4 January 1988 and 2 April 2003. At the end of the study statistically, significant and higher returns are seen on Thursdays and Fridays compared to other days; whereas lower returns are observed on Mondays.

1.2.1.1.2. Intraday Effect

Harris (1986) investigates intraday effect for 1616 stocks between the dates 1 December 1981 and 31 January 1983 by dividing a trading day into 24 parts which is fifteen minutes each. Considerable amount of difference is found between the first 45 minutes of Monday and first 45 minutes of other trading days. Furthermore on

Mondays, it is observed that at the first 45 minutes prices fall. On other days, prices rise sharply particularly at the end of trading day.

1.2.1.2. Monthly Anomalies

In the framework of monthly anomalies, authors examine if stock returns indicate different trends.

1.2.1.2.1. January Effect

"January Effect" phenomenon in stock markets is used to mention the case in which investors get higher and positive abnormal returns in January compared to other months.

Based on article written by Özer and Özcan (2002), pricing behavior of stocks in January shows two characteristics:

- Investors have higher returns on January, compared to other months on stock market.
- Investors purchasing small market value stocks, tend to earn more than other investors who are purchasing large market value stocks. (Özer and Özcan,2002:134)

In spite of the fact that January effect was firstly observed by Watchel in 1942 who documents higher stock returns for January; it is suggested that Rozeff and Kinney are the first ones that discover it in 1976. Their study makes much more effect on literature with its systematic and results. They observe that higher returns are obtained on January than other months. Average monthly return of January is specified as 3,48 percent, whereas other months averaged as 0,42 percent. Rozeff and Kinney (1976) attribute higher rates of return acquired in January in U.S stock market to seasonal accounting information lags which may affect risk premiums on seasonal basis. (Schneeweis and Woolridge, 1979:942)

Branch (1977) attributes unusual January stock returns to sale of securities for tax purposes.

Reinganum (1983) examines if January effect might be explained by tax-loss-selling hypothesis. He explains that magnitude of price increase realized at the first week of January, is positively related with magnitude of capital losses realized at the end of previous year. It is also concluded that average stock returns are higher at the first five days of the calendar year.

Shefrin and Statman (1985) explain that investors prefer to sell their losers in December as a self control measure. They suggest that investors are reluctant to sell for a loss even on December which is deadline for realizing losses but do it to recognize tax benefits.

Sias and Starks (1997) explain reasons of January effect under two headlines: "Tax-loss selling hypothesis" and "Window dressing hypothesis". According to Tax-loss selling hypothesis; individual investors tend to sell stocks that have declined in value to realize tax losses prior to year end. Those sell transactions lead bid prices to decline at late Decembers. Because of that reason, on last a few days of December returns are generally small or negative. And after investors' desire to realize losses disappear on first days of January; stock prices tend to increase resulting in positive returns. According to window dressing hypothesis; institutional investors tend to buy winners and sell losers prior to calendar year-end to present respectable year-end portfolio holdings.

Keim (1983) provides findings proving the existence of a significant and negative relationship between firms' size and returns acquired in January.

Roll (1983) implies that approximately half of the January Effect happens between the last trading day of December and first four trading days of January.

In the first studies conducted, it is so noteworthy that not only January effect but also firm size effect is observed. Even in this framework; Keim (1983), Reinganum (1983), Roll (1983) mention that January Effect is peculiar to small market value firms.

Özer and Özcan (2002) investigate existence of January effect in ISE by using monthly returns for the years 1988-1997. They mention that returns acquired in January are higher than all months except for June. Although difference exists between returns of January and June, that difference is not statistically significant.

Researches conducted indicate that January Effect is valid not only for stock markets but also for other financial asset markets like option market, bond and bills market. January effect is observed in all studies in different markets as listed below. (Özer and Özcan, 2002: 136)

- Wilson&Jones (1990)- January Effect is detected for both corporate bonds and commercial papers.
- Schneweis&Woodridge (1979)- They find evidence of monthly seasonality in municipal, corporate, public utility , government bonds. Higher returns are found for January and October.
- Smirlock (1985) finds no evidence of seasonality for government and high-grade corporate debt instruments. Nonetheless, he concludes that higher returns are obtained on January for low-grade corporate bonds.
- Dickinson and Peterson (1989) investigate January effect for call and put options. They record higher significant returns in early January for call options. They conclude that put options show less seasonality.

1.2.1.2.2. Intra Month Effect

Studies about intra month effect investigate if there is a return difference between first half of the month and second half of the month.

Ariel (1987) is the first one who makes comprehensive research on this topic. He compares average stock index return of first nine and last nine days of each month for New York Stock Market for the period 1963-1981. He concludes that positive average returns are only acquired at the first half of months. In another words, all of the cumulative increases are observed at first half of the month during the nineteen year studied**.** During second half of the month no contribution to cumulative increase is observed. Ariel also suggests that intra month effect is strongest at the last four days of the month and first four days of following month.

Barone (1990) makes research for the period 2 January 1975-22 August 1989 in Italian stock market. He finds that stock returns decrease at the first half of the month and increase at the second half of the month.

1.2.1.2.3. Turn of the Month Effect

If it is possible to get higher returns on last days of the month and first a few days of the subsequent month, turn of the month effect is said to be exist in this market. Many studies made shows that higher returns are earned on the last 1-4 days of the month and first 1-4 days of the subsequent month. (Barak, 2006:143)

Ariel (1987) divides month into two parts, first part starting from last day of the prior month. He records negative returns for latter half of the month. He also concludes that considerable amount of stock returns realized between last trading day of the prior month and following months' first nine trading days.

Lakonishok and Smidt (1988) examine Dow Jones industry index between the years 1897 and 1986. Returns for the four days around the turn of the month, starting last trading day of prior month is found as 0.473%. Four days constituting turn of the month is higher than average monthly return that is 0.35%. By this way existence of turn of the month effect is proven.

1.2.1.3. Yearly Anomalies

1.2.1.3.1. Turn of the Year Effect

As Keim (1983) finds that a large part of differential risk adjusted returns of small company stocks appear in the first week of January, "turn-of-the-year effect" becomes a popular research area. Turn of the year effect could be explained by tax effect as Schwert (1983) explained. He documents that some investors sell securities at year end to establish short-term capital losses for income tax purposes. That "selling pressure" may cause stock prices to depreciate at the end of the year and at the first week of the subsequent year stock prices increase. It is suggested that case become so commonplace that it was discussed at column of “Heard On Street” in Wall Street Journal. (Schwert ,1983:7)

1.2.1.4. Anomalies Related to Holidays

In many countries, higher stock returns are realized before and after the periods when stock market is closed, namely before and after holidays. These holidays includes not only official holidays and weekend holidays but also religious holidays.

Robert Ariel (1990) examines the returns of 160 days that preceded holidays for the years 1963-1982. For equal-weighted index, he documents the mean return on pre-holidays and on other days as 0.529 % and 0.056% respectively. On the other hand, for value-weighted index that numbers are 0.365% and 0.026 %. Both results are statistically significant.

Kıyılar and Karakaş (2005) could not detect any holiday effect in the study they conducted.

1.3. SECTIONAL ANOMALIES

1.3.1. Size Effect

Size effect which refers to negative relation between security returns and market value of common equity of a firm is one of sectional anomalies on which growing number of articles are written.

Standard asset pricing models that have an important place on contemporary finance, base on the assumption that individual are risk averse. They assume a positive relation between asset’s risk and its expected return. However, statistical association between risk and average returns is found only marginally significant in fundamental articles like Sharpe (1964), Lintner (1965), Black (1972)**.** (Schwert, 1983:4) Due to this weak association, new benchmarks are started to be examined. As a result of those examinations, Fama and French (1992) conclude that not only beta but also firm size and book to market equity explain the variation in cross-sectional expected returns. However pioneer papers about size effect are written by

Banz (1981) and Reinganum (1981) in early 1980s. After then, size effect has become a popular research area.

According to Banz (1981) and Reinganum (1981), small firms earn higher returns than large firms on average. In other words, they state that high market value firms provide lower risk adjusted returns. However, Chan and Chen (1988) document that size effect is an artifact of large measurement errors in betas that allows firm size to serve as a proxy for true beta. They also add that when more accurate beta estimates are used, size related differences in average returns will be no longer observed. After estimated betas are controlled, firm size proxy will no longer has explanatory power for averaged returns across size-ranked portfolios. Authors observe size effect only when five years of data is used to estimate betas. However when a longer period of time data is used; firm size variable no longer has explanatory power. Jegadesh (1992) mentions that size effect could be attributed to measurement errors in betas, nevertheless he also adds that above studies could be even spurious. He suggests that it is difficult to attribute differences in average returns to firms' size or beta when these variables are correlated. To prove it, he constitutes test portfolios in which correlation between betas and size proxy is small and he concludes cross sectional differences in average returns could not be explained by betas for these portfolios. He also states that same result is valid when betas estimated with annual returns.

1.3.2. Book Value/Market Value Effect

That anomaly refers to higher returns that higher book-to-market value firms (value stocks) get compared to low book-to-market value firms (growth stocks). Findings proving that anomaly is firstly written by Stattman (1980) and Rosenberg et all (1985). Both find positive relationship between average stock returns and book-to-market value in US common stock market.

Chan, Hamao, Lakonishok (1991) investigate the relationship between expected returns and four variables including size, book to market ratio, cash yield and earnings yield. They conclude that book to market ratio and cash flow yield have the most significant positive impact on expected returns. They also find book to market ratio as the most statistically and economically important variable.

Fama and French (1992) state that book to market value of a firm's equity capture some part of the variation in average stock returns. They evaluate this ratio as capturing some sort of rationally priced risk. Other variables combining book-to-market value to capture variations in stock returns are beta, size, leverage, E/P ratios. Since authors are interested in investigating impact of leverage on stock returns in the beginning, they only include non-financial firms in their analysis. Yet they find size and book-to-market ratio as strongest predictors of stock returns.

Black (1998) asserts that is not surprising that firm with high book to market ratio shows poor subsequent accounting performance. But Black does not think it is an evidence of priced risk factor. Success of this ratio is attributed to market inefficiencies rather than "priced factors" Fama and French favor.

Chui and Wei (1997) examine the relationship between expected stock returns and beta, book-to-market equity, size in Hong Kong, Korea, Malaysia, Thailand, Taiwan markets. They find no evidence for positive relationship between expected return and beta; they only find a weak relationship. They conclude that stock returns are more related to size and book to market ratio. They state cross-sectional variations of expected returns can be explained by book-to-market equity in Hong Kong, Korea, Malaysia. They also find a significant size effect in all markets except for Taiwan.

1.3.3. Price Earnings Ratio Anomaly

Price/Earnings ratio shows the amount that is required to pay for each unit of expected earnings. Price earnings ratio is accepted as an important indicator of future performance of a stock. Low price/earnings ratio stocks tend to get higher returns than high price/earnings ratio stocks. If that ratio is below one for a stock, that stock is advised to be bought.

Basu (1977) examines relationship between E/P ratio and performance of equity securities for the period 1956-1971. Author finds that low P/E portfolios on average get higher absolute and risk adjusted returns than high P/E portfolios**.** Performances of portfolios author founded are measured by using Jensen, Sharpe and Treynor performance criteria**.**

Reinganum (1981) investigates the relationship between E/P anomaly and market value anomaly as a separate section in his study. Within the sample used, it is observed that small firms systematically experienced larger rates of return than large firms with equivalent beta for at least two years. Even after controlling returns for any E/P effect, firm size effect still exists. However after controlling returns for market value effect, E/P effect no longer exists.

1.3.4. Neglected Firm Effect

Various studies indicate that stocks that are less frequently advised by experts or that have small trading volume tend to have better performance than other stocks. That effect is defined as neglected firm effect. Pioneer research in that area is prepared by Bauman in (1964) and (1965) which show that unpopular stocks have better performance than popular stocks.

Karan (2000) investigates neglected firm effect by using monthly data for the years 1996-1998. He classifies stocks as popular ones and neglected ones. Then he looks up systematic risks and returns of stocks after one month from classification. Author finds that neglected firm stocks have lower systematic risk than large company stocks. Another finding is that investors investing in neglected firm stocks get higher risk adjusted returns than popular stocks.

1.4. TECHNICAL ANOMALIES

Technical analysis method aims to estimate future security prices by examining past prices.

Technical analysis stands two assumptions: (Gençay and Stengos, 1997:23)

- Behavioral pattern of the market is said to be not changing much overtime, especially when long-term trends are considered. Even if future events could be very different from past events, the way market respond uncertainties and how handles them do not change very much. Because of that reason patterns in market prices could be used for predictive purposes.

- Due to fact that relevant information could be distributed fairly efficiently, but not perfectly; investors have an opportunity to maximize their profits or minimize losses via superior analysis.

Technical analysis sometimes introduces findings that contradict with efficient market hypothesis. These findings are said to be technical anomalies. Parallel to study of Pompian (2006), moving averages and support and resistance anomalies will be examined under the topic of technical anomalies.

1.4.1. Moving Averages

Moving average method aims to detect a new trend that is developing in the market or signal showing end of an old trend. It is basically a smoothing mechanism. It involves lagging. When moving average is shorter, it lags less and follows market more closely. In contrast, a longer moving average is less sensitive to fluctuations in the market and said to be lagging more behind market.

A Moving average is computed by computing averages of a specific number of consecutive observations. By moving average method, seasonal variations in the data are aimed to be smooth out.

Brock et all (1992) conclude that technical rules have predictive ability in Dow Jones Index for the period 1897-1986. They provide strong support for technical analysis. According to variable moving average rule of Brock et all, buy (sell) signals are initiated when short run MA is above (below) long run MA. Whereas fixed MA rule states that when short run MA cuts the long run MA from below (above), buy (sell) signal is generated. As a conclusion when prices are higher compared to variable moving average buy strategy should be followed; otherwise sell strategy should be followed. By this way, higher returns compared to buy-and-hold strategy could be attained.

Hudson et all (1996) repeat same study based on UK data. Authors conclude that it is possible to predict future prices by technical analysis. However, they also conclude that excess returns could not be made by technical analysis when trading is costly. Authors conclude that buy signal offer positive returns, on contrast to negative returns offered by sell signals. Moreover, sell signals sourced by technical analysis are found to be having more predictive ability then buy signals. For last, long periods are needed for predictive ability to be displayed.

1.4.2. Support and Resistance

Support is the bottom point occurred in the past, whereas resistance is the peak point of the past. (Çetinyokuş and Gökçen, 2002:48) Movements observed at those points are very essential. When support point is broken downward, a new trend starts. This case should be continued with a sell signal. If price is reversed from support point, downward trend ends. If prices pass resistance points, upward trend continues. Price that passes resistance points is perceived as a buy signal. If price reversed from resistance points, upward trend is said to be failed.

Brock et al (1992), state that usage of support and resistance points provide investors to get higher returns. Curcio et all (1997) suggest that no significant profit is generated once transaction costs are taken into account.

1.5. PRICING ANOMALIES

1.5.1. Under reaction

Barberis et al (1998) express underreaction as higher average returns of a stock in the period following good news compared to average returns attained in the period following bad news. This is a mistake which is corrected in the next period.

Over short time periods like 1-12 months, security prices tend to underreact to news. (Barberis et al, 1998:307) In that case news is incorporated into prices slowly, not immediately and they exhibit positive autocorrelation over this time period. News which could be good or bad and that is heard in period t is symbolized by Zt. If news is good denoted by Zt=G, if not Zt=B, underreaction could be formulized like this: (Barberis et al, 1998:311)

$$E(r_{t+1} \mid z_t=G) > E(r_{t+1} \mid z_t=B) \qquad \textbf{(2)}$$

1.5.1.1. Literature of Underreaction Hypothesis

Bernard and Thomas (1990) examine actual properties of time series of earnings. Mentioned series is changes in company earnings in a specific quarter compared to same quarter of previous year. Authors use a sample including 2626 firms for the period 1974-1986. Autocorrelations exhibited on series are respectively: 0.39 at a lag of one quarter, 0.19 at two quarters, and 0.06 at three quarters and -0.24 at four quarters. This shows that earnings have indicated a slight trend over first quarter, second quarter, third quarter horizons and a slight reversal after a year. After they examine findings they find, Bernard and Thomas assert that market participants do not recognize positive autocorrelation in earnings changes and they consider earnings to follow a random walk. This belief led them to underreact earnings announcements.

Cutler et al (1991) examine returns on bonds, stocks, foreign exchanges, real estate, collectibles and precious metals in different markets for the period 1960-1988 and find positive autocorrelations in excess index returns for shorter periods like a time horizon between one month and one year. Most of autocorrelations are found significant. Findings are in consistence with under reaction hypothesis.

Bernard **(**1992) practices a survey which aims to determine if investors underreact to news about company earnings. Author measures earnings surprise by standardized unexpected earnings (SUE) which is defined as the difference between actual earnings and forecast scaled by historical standard deviation of forecast errors. Author concludes that information about earnings is incorporated into prices. Another finding is that stocks with higher earnings surprises, continue to earn higher returns in the period after portfolio formation. This means earnings announcements are under reacted by market in revising company’s stock price. To prove that author gives an example; stocks with highest SUE earn a cumulative risk-adjusted return which is 4.2% higher than return of stocks with lowest SUE over the 60 trading days after portfolio formation. And he makes an inference that SUE or past earnings announcement return has power to predict future risk adjusted returns. In other words, information about earnings is said to be only slowly incorporated into prices.

Jegadeesh and Titman (1993) find that strategies, involving buying stocks which performed well in the past and selling stocks that performed badly in the past , obtain significant positive returns over 3 to 12 month holding periods in the study they prepared on US stock market. This means prior winners tend to earn more in holding period, whereas prior losers tend to continue to lose. This proves that reaction to stocks is not given immediately, but given gradually. Namely underreaction is about issue.

Chan, Jegadeesh, Lakonishok (1996) form ten portfolios based on prior six-month returns to document stock price performance, in which portfolio one is “past losers” and portfolio ten is “past winners”. Over subsequent six months, difference of return between portfolio one and portfolio ten is measured as 8.8 percent which proves availability of return momentum in stock market. Profitability of momentum strategies cause market to react earnings announcements slowly, namely they cause under-reaction.

1.5.2. Overreaction

Overreaction stocks give to news that occurs in the same direction consistently is defined as overreaction anomaly in the literature. It is generally observed over longer time periods like 3-5 years. In stock market, stocks on which a long history of good news exists have a tendency to become overpriced and low average returns are observed afterwards. Namely, securities with strings of good performance receive extremely high valuations and these valuations on average return to the mean. (Barberis , 1998)

Barberis et al (1998) express overreaction as occurring when the average return following a series of announcements of good news is lower than the average return following a series of bad news announcements. Here the point is that as a result of series of good news are announced, investors become far more optimistic about continuity of good news and so overreacts which will cause stock prices to rise extremely high levels.

The most important studies criticizing efficient market hypothesis is prepared by Debondt and Thaler (1985, 1987). They obtain results contradicting with efficient market hypothesis in the study in which they used data of 1933-1980 and announced existence of a new anomaly.

Debondt and Thaler (1985) suggest two hypotheses:

- Extreme price movements in stock prices will be followed by subsequent price movements in the opposite direction.
- The more extreme the initial price movement, the greater will be the price adjustment.

Both hypotheses mentioned violates the weak-form efficiency which is the weakest level of efficiency. According to weak-form efficiency, it is impossible to get abnormal returns by using past data. However in overreacted markets, it is possible to get abnormal returns by using price reversals. This strategy is called contrarian strategy.

According to Barberis (1998) since it is possible to earn higher returns by exploiting underreaction and overreaction without taking on extra risk, pricing anomalies pose a challenge to efficient market hypothesis.

Debondt and Thaler (1985) examine overreaction hypothesis from a behavioral perspective. By referencing Kahneman and Tversky they explain that Bayes Rule is not an appropriate characterization of how individuals respond to new data. In Bayes rule, individuals make decisions by considering possibility revisions as new information comes. Debondt and Thaler (1985) conclude that rather than following Bayes Rule, individuals inclined to overweight recent information and underweight prior (base rate) data in updating their beliefs. Overweighting recent positive (negative) information will cause stock prices to reach extremely high (low) levels. As a result of overreaction if stock prices overshoot systematically, then only past return data will be sufficient to predict price reversals. Accounting information as earnings will be no longer useful.

Debondt and Thaler (1985) formulize efficient market of Fama (1970) like this:

$$E(R_{jt} - E_m(R_{jt} \mid F_{m\,t-1}) \mid F_{t-1}) = E(\tilde{u}_{jt} \mid F_{t-1}) = 0 \qquad \textbf{(3)}$$

In the formula above; Ft-1 symbolizes complete set of information at time t-1, Rjt symbolizes return on security j at time t, $E_m(R_{jt} \mid F_{m\,t-1})$ represents the expectation of Rjt assessed by the market conditional on the information set Fmt-1.

Namely, efficient market hypothesis implies that $E(\tilde{u}_{wt} \mid F_{t-1}) = E(\tilde{u}_{Lt} \mid F_{t-1}) = 0$ where $\tilde{u}_{wt}$ represents mean return of winner securities who performed well in the past and $\tilde{u}_{Lt}$ represents mean return of loser securities which performed poorly in the past. Debondt and Thaler (1985) determine winners and losers based on past excess returns, namely based on the abnormal positive and abnormal negative returns observed in prior period. However, according to overreaction hypothesis winner portfolio (loser portfolio) obtains negative (positive) returns in test period. This is formulized by Debondt and Thaler as;

$$E(\tilde{u}_{wt} \mid F_{t-1}) < 0 \text{ and } E(\tilde{u}_{Lt} \mid F_{t-1}) > 0 \qquad \textbf{(4)}$$

1.5.2.1. Behavioral Finance Models Explaining Overreaction Hypothesis

1.5.2.1.1. Representative Agent Model

According to that model founded by Barberis, Shleifer ve Vishny (1998), investors are not rational. They tend to be affected by two mistakes of judgment. Reaction which they give depends on the type of the mistake of judgment they affected. These mistakes of judgments are “conservatism” and “representativeness”. Barberis et al (1998) explain conservatism as tendency of individuals to change their beliefs slowly in the face of new evidence. They show resistance to change their beliefs which causes underreaction in stock prices. Similarly, Döm (2003) defines representativeness heuristic as a judgment strategy which assigns probability to a thing based on how much it meets a specific stereotype. She adds that representativeness heuristic may cause people to reject or ignore relevant information. Since representativeness heuristic causes investors to overweight recent noteworthy information and underweight population statistics, it could cause overreaction.

According to model, firms' earnings are inclined to stay in the same regime rather than to switch in any given period. At the end of each period, earnings are observed and investors update their beliefs regarding the state it takes place. For instance if a positive news is followed by other positive news, investors more likely to consider that it is in trending regime. Namely, overreaction takes place when investors believe that a trend begins after subsequent good news. Nonetheless, if positive news is followed by negative news they are more likely to consider that it is in mean-reverting regime. Here, investors tend to believe that there will be changes in profits and they underreact.

1.5.2.1.2. Overconfidence and Biased Self-attribution Model

This model is developed by Daniel, Hirshleifer ve Subrahmanyam. It is developed on two psychological biases: Overconfidence about precision of information and biased self-attribution that causes asymmetric shifts in investor's overconfidence depending on their investment outcomes. (Daniel et al., 1998:1839) Overconfidence for financial markets implies that investors perceive themselves more talented to value securities than they actually are and they underestimate variance of their forecast error. Whereas biased self attribution is the tendency of investors to build an association between overconfidence on his private information and investment performance. (Ülkü, 2001:107) Biased self-attribution comes into being when investors' information is in consistence with public information.

Central theme of this model is that private signals are overreacted by stock prices, on contrary public signals are underreacted by stock prices. (Daniel et al., 1998:1841) Parallel to that theme overconfidence is expected to cause underreaction, whereas self-attribution bias is expected to cause overreaction.

In contrast with common view seeing positive (negative) autocorrelation as an indicator of underreaction (overreaction), Daniel et al (1998) indicate that positive return autocorrelations could be a result of continuing overreaction.

1.5.2.1.3. Hong and Stein Model developed on interactive relationship between heterogeneous investors

In the model that is developed by Hong and Stein (1999), there are two types of investors who are both boundedly rational: news watchers and momentum traders. Each type is only able to process specific type of information. News watchers use signals regarding future fundamentals they privately observed, but not current or past prices to make forecasts. On contrary momentum traders use history of past prices to make forecasts. (Hong and Stein, 1999:2144) When only news watchers are active in the market, underreaction is observed. Nonetheless, when momentum traders are added underreaction disappears via arbitrage. Momentum traders attempt to profit from underreaction creates overreaction after a point. (Hong and Stein,1999:2145)

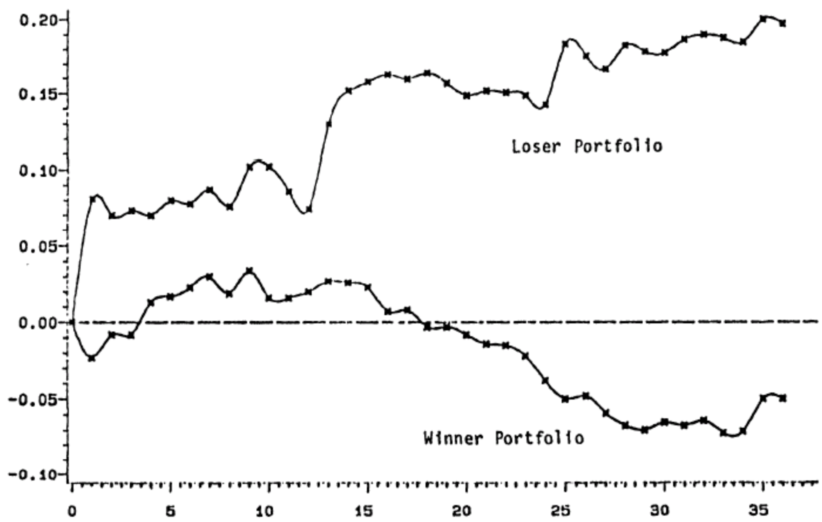
1.5.2.2. Literature of Overreaction Hypothesis

Pioneer study is prepared by Debondt and Thaler in 1985. In that study authors conclude that portfolio of stocks on which poor returns are observed over previous five years (portfolio formation period), outperform portfolio of stocks on which extremely high returns are observed over the same period at subsequent five years (test period). Authors call this violation to Efficient Market Hypothesis “Overreaction” concept since investors overreact in the first period and correct themselves in subsequent period. Debondt et al (1985) observe that losing stocks have earned approximately 25% more than winners after thirty-six months from portfolio formation. Moreover they conclude that overreaction effect is asymmetric; since it is larger for losers than it is for winners. Finally, authors conclude that most of the excess returns are observed on January but only by loser portfolios. (It could be seen in the graph below) A criticism to results of Debondt and Thaler has come from Jegadeesh and Titman (1993). They state that it is not clear if results Debondt and Thaler find are simply attributed to overreaction since excess returns are only acquired by long-term losers. (Jegadeesh and Titman, 1993:65)

Figure 2

Average of 16 year test periods between Jan1933-Dec 1980

Length Of Formation Period: 3 Years



Months After Portfolio Formation

(Debondt and Thaler, 1985: 800)

Second important research is also prepared by Debondt and Thaler in (1987). In that study by following the same methodology, authors find that excess returns which losers get in the test period, and particularly in January, are negatively related with both long term and short term formation period performance. Authors also document that winner-loser effect can not be attributed to changes in risk which is measured by CAPM-Betas. Authors conclude that small firm effect is partly observed as a losing firm effect, but they also state that even if losing firm effect is removed excess returns to small firms still exists. Finally, earnings of winning and losing firms show reversal patterns that are in consistence with overreaction hypothesis. Authors proved that view by stating a dramatic fall (rise) in stock prices is predictive of a subsequent rise (fall) in company specific earnings.

Howe (1986) examines behavior of stock returns in the study he prepares by using weekly data for the period 1963-1981. In this study he classifies stocks as the ones with good news and the ones with bad news. Good news sample includes 385 observations involving 299 different countries, whereas bad news sample comprises 131 observations and 118 companies. At the end of study, he records findings supporting overreaction anomaly.

Brown and Harlow (1988) investigate overreaction hypothesis for security returns from Center for Research in Security Prices (CRSP) for the period between January 1946 and December 1983. In that study extreme price movements are examined as a sign for overreaction. Authors define extreme price movements as stocks with residual returns that gain or loss between 20-65 percent in absolute value between one to six months. To conclude, although large price reversals are shown for losers, winners do not show any price decline subsequent to first month.

Fama and French (1988) examine stock returns' autocorrelations for increasing holding periods. Large negative stock return autocorrelations, which are in consistence with overreaction hypothesis, are recorded for horizons longer than one year.

Zarowin (1989) prepares a study by using data between 1971 and 1981 in US stock market. Author asserts that if market participants consider extreme earnings changes of firms to be permanent, they will overreact by bidding stocks prices of good (bad) performers up (down) too high(low). However, participants will understand their mistakes when subsequent earnings realizations are not extreme. According to results, stock returns of poorest earners outperform best earners over 36 months subsequent to extreme earnings year. However, it is considerable that poorest earners are generally small size firms and author suggests that when groups are matched by size, return differential disappears. This means when equal size poor and good earners are matched, little difference is observed on return behavior. Small firms show better performance than large firms and smaller winners tend to show better performance than large losers. Thus, author attributes return difference observed to size effect rather than investor overreaction to earnings.

Seyhun (1990), acquires findings that supported overreaction in the study in which he examines insider trading activity around 1987 Crash. At the end of study, he indicates that investors could extremely overreact in crises periods. He claims that even corporate insiders who are the most knowledgeable ones about fundamentals of firms could not foresee the Crash and purchase stocks, whose prices declined more during Crash, rather than selling. At the end of study large positive returns are observed in 1988 in the stocks that were purchased more extensively by insiders during October 1987.

Chopra, Lakonishok and Ritter (1992) corroborate findings of Debondt and Thaler (1985). They investigate stock returns of NYSE, incorporate size, prior returns and betas for years 1926-1986 by using multiple regression models. At the end of study, authors document an economically important overreaction effect even after adjustments for size and beta are made. Moreover extreme prior losers are found to outperform extreme prior winners by 5-10% per year during the subsequent five years. Overreaction effect is found stronger for smaller firms. Finally it is concluded that even though it could not be explained by tax-loss selling, January effect is observed.

Conrad and Kaul (1993) assert that high returns acquired by Debondt and Thaler (1985) stems from the methodology used. They state that returns to typical long-term contrarian strategy are upwardly biased, since single period returns over long intervals are calculated. They assert that not only true returns but also upward bias in single period returns are cumulated in cumulation process. In the study in which they used holding period return rather than cumulative abnormal return, they could not find evidence for overreaction hypothesis.

Wong (1997) examines short-term over reaction anomaly by using daily data between the years 1986-1995 for the markets of USA, HongKong, Taiwan, Singapore, Thailand, Australia, Philippines, Japan, and South Korea. That study documents significant 5-day,10-day and 20-day cumulative abnormal returns following large one day declines/advances in some Asian emerging markets like Hong-kong, Singapore, Taiwan, Thailand, Australia, Philippines. Stock prices are inclined to increase after large one-day advance and decrease after large one-day decline. Authors conclude that these findings do not support overreaction anomaly in the short-term.

Kang et al (1999) conclude that although stock price-reactions to convertible debts and issues is not negative for Japanese firms, issuing firms performed poorly compared to non-issuing firms. Although issuing firms do not experience significant negative abnormal returns when issue announcement is made, underreaction is observed for issuing firms. Mentioned underperformance is strongest for firms issuing public convertible debt. An interesting finding is that contrary to US market findings, poor performance is not concentrated on small firms or firms with high market to book ratio.

Baytaş and Çakıcı (1999) investigate overreaction hypothesis in seven industrialized countries including USA, Canada, UK, Japan, Germany, France, Italy. Authors find evidence of overreaction in all countries except for USA, but they conclude that overreaction in Canada is relatively weak. Low-price portfolios are observed to outperform market consistently, whereas high-price portfolios obtain a return that is below aggregate market.

Ülkü (2001) explained availability of articles about under-reaction and overreaction which are proven by short-term positive or long-term negative autocorrelation findings. He states that momentum strategies are developed to benefit from short-term positive autocorrelation, whereas contrarian strategies are developed to benefit from long-term negative autocorrelation. He concludes that these strategies are tested and found as profitable. (Ülkü, 2001:102)

Durukan (2004) investigates long-term overreaction effect in ISE by using monthly data for the period 1988-2003. At the end of study, findings that are inconsistence with overreaction hypothesis are found. Author also concludes that returns from loser portfolio and price reversals are higher relative to winner portfolio. Author attributes that case to tendency of investors to overreact to bad news more extremely than they overreact to good news and sell stocks because of their fear to lose.

Barak (2008) examines overreaction hypothesis in ISE for the period January 1992- December 2004. He finds consistent results with other studies. He forms 5-year winner and loser portfolios and observes performance of them during subsequent five year. He finds that portfolio of winners of past become losers or may provide lower returns at subsequent period, whereas portfolio of losers become winners at subsequent period.

1.6. POLITICAL ANOMALIES

Anomalies that are dependent to political factors examine abnormal return differences that are acquired in general election periods and in the periods in which parties with varied political views establish the government. (Demirelli, 2008:225) Political risk increases as government intervention to economy increases. Such interventions could be realized in many ways like barriers government put into cash flows to country, controls they practiced on foreign exchange and portfolio flows, taxes. Political instability, elections, government changes and bribery events are other types of political risks. (Mandacı, 2003:3)

Mandacı (2003) has investigated the effect of general elections on return of ISE-100 index. ISE-100 index returns on fifteen days before and after general elections are examined. Four general election periods are taken into consideration. These are 20 December 1991, 24 December 1995, 18 April 1999, 3 November 2002 general elections. In the study, event study method is benefited. With the help of that method abnormal returns that take place on fifteen days before and after general elections are calculated and statistical significance of that returns are tested. Fifteen days before and after general elections are selected as event window, because it is thought that effects of elections are short-lived in developing markets like Turkey. At the end of the study, abnormal returns are observed in a few days after elections except for the 1991 general elections. Abnormal cumulative average returns acquired after elections are found statistically significant. Only for 1995 elections, same results can not be found. Author attributes that situation to negative impact of financial crisis that was lived in these years. Besides, none of the abnormal returns that take place before elections are found significant.

1.7. BEHAVIORAL DISCUSSIONS REGARDING EFFICIENT MARKET HYPOTHESIS: NOISE TRADING

Noise concept is firstly explained by Black (1986). In his study; he states that although people usually trade on information, sometimes they trade on noise as if it is information.

He explains importance of noise from perspective of trading volume. He states that if “noise trading” does not take place, there will be so little trading. Only the people who want to spend or who want to invest their cash, will have made transactions. He asserts that if both sides of the trade know the same information, one side must be making a mistake. If side making mistake declines to trade, trading on information will no longer take place.

The more noise trading takes place, the more liquid markets will be. (Black, 1986: 6) This is the case due to frequent trades. Noise trading could also cause noise to be reflected in prices. As a result, price of a stock not only reflects information but also noise. As noise trading more frequently takes place, it will become more profitable for people to trade on information, but this is only the case because prices incorporate noises. In most cases, noise traders will lose money by trading, whereas information traders will earn money at the same time.

Information trading increases does not mean more efficient prices. Reasons could be counted like:

- Information traders can not be sure about the size of the position they must take to eliminate the noise. Even if they can determine the size, there is a limit of size that investors could take. Because taking a larger position means taking more risk.
- Information traders could never be sure that if they are trading on information or noise. Information they trade on could already have been reflected into prices. If this is the case, trading on this information will be just like trading on noise. (Black,1986:6)

Delong, Shleifer, Summers and Waldman (1990) states that unpredictability of noise trader's beliefs, increases risk in the market which deters arbitrageurs to take position against them. Authors suggest that noise traders provide higher expected returns than rational investors by trading on noise. Nonetheless, they also have to bear more risk.

Noise trading concept contradicts with efficient market hypothesis in the framework of arbitrage. Efficient market hypothesis assumes that irrational investors' trades are met by rational arbitrageurs who eliminate irrational investors' influence on prices. On contrary, Shleifer and Summers (1990) assert that arbitrage does not completely counter responses of prices to fluctuations in uninformed demand. They explain that there are two types of risk which limit arbitrage. First one is fundamental risk. It involves that selling "overvalued stocks", which are selling above expected value of future dividends, is risky since there is always a chance for market to do very well. Possibility of such a loss limits original position of the arbitrageur and keeps his short-selling from bringing prices back to fundamentals. Second risk is the unpredictability of future resale price. It refers; arbitrageur who sells short overpriced securities takes on the risk that stocks may be more overpriced in the day when arbitrage trade is put on than they are today. Again, possibility of such a loss limits size of arbitrageur's initial position and keeps him from driving prices to fundamentals.

CHAPTER TWO
BEHAVIORAL FINANCE

In this chapter of the study, development behavioral finance is examined by making comparisions with traditional finance. Related concepts will be also mentioned.

History of academic finance includes three eras: old finance, modern finance, new finance. In old finance era which dominates to finance world until mid-1960s, financial statement analysis are being made based on accounting rules. Modern finance era; during which CAPM, efficient market hypothesis are developed; starts with 1950s. And in early 1990s, in new finance era inefficiency of markets are tried to be proven by using statistics, econometrics and psychology. As it could be seen that finance is separated from accounting where it takes it roots from. Also in the new finance era, psychology is started to be taken into consideration.

Traditional finance, which is related with rational solution to decision problem and explains how investors should behave, has been developed in a normative manner. On the contrary behavioral finance, which concerns how people actually behave in financial decision-making, is developed in a descriptive manner. Thaler (1993) calls behavioral finance “open-minded finance”, since it accounts the possibility that some individuals in the economy are not fully rational. Behavioral finance could also be explained as application of psychology to financial behavior. (Baker, Nofsinger, 2002:98) Different from traditional finance, in which model is generated initially and its accuracy is examined empirically then, in behavioral finance market behavior is observed initially and model is generated afterwards.

Academicians, who think that traditional finance models are inadequate to explain the way things are in financial markets, support their models with findings of cognitive psychology. These studies are called behavioral finance. (Bostancı: 2003) Behavioral finance begins with criticism of financial theories.

First criticism of behavioral finance is on definition of rational individual. Based on behavioral finance, people are normal and assumed to have bounded rationality. It asserts that people have some cognitive bias and their behaviors are affected by their feelings and bias. Daniel and Titman (1999) also mention that investors do much of their analysis by considering “hunches” or “feelings” that could be affected by behavioral biases. They attribute this case to limitedness of human cognition.

Bounded rationality of people causes deviations from rationality. Not only individual investors but also portfolio managers deviate from rationality. For instance, portfolio managers may show herding behavior and may select same stocks with other managers. By this way, they believe that they eliminate the possibility of looking bad compared to other managers. Moreover they may involve in window dressing. In order to look good to investors who examine end of year reports, they may include stocks that have done well and sell the ones that have done poorly.

On contrary to traditional finance which assumes that people always make optimum preferences; behavioral finance asserts that people always could not make optimum preferences. According to behavioral finance, they tend to choose the alternative which satisfies them rather than the alternative that maximizes their utility. Bostancı (2003) infers same thing by saying that investors not only take risk and returns into consideration, but also they take other variables into account. He also notes that evaluation of variables is not a perfect process.

In the “Handbook of Experimental Economy” which is written by John Hagel and Alvin Roth, authors also state that people do not behave in a way that is in consistence with basic economic theories like theory of utility.

Second criticism of behavioral finance, is about randomness of investor trades. Based on efficient market theory, irrational investors trade randomly in a way that offset each others’ effects. That assumption also relies completely on rationality of investors. But this is not the case. Shleifer (2000) asserts that people deviate from rationality not randomly, but they mostly deviate in the same way. Since unsophisticated investors (noise traders) constitute their demands for securities based on their beliefs, their buying and selling could be highly correlated. This case becomes more severe when noise traders follow each other's mistakes by using same rumours.

Arbitrage which is a fundamental concept in finance is defined as "the simultaneous purchase and sale of the same, or essentially similar, security in two different markets for advantageously different prices". (Sharpe and Alexander, 1990) Bodie et al (2009) define arbitrage activity as "simultaneously buying asset where it is cheap and selling where it is expensive." By doing this arbitrageurs are assumed to increase price where it is low and decrease where it is high. Namely they bring prices into fundamental values and keeps market efficient, until arbitrage opportunity is eliminated. However that is not the case in real world. Behavioral finance asserts that there are not arbitrage opportunities that are foreseen on theory. Contradicting with efficient market theory, real-world arbitrage is limited and risky. This is due because effectiveness of arbitrage depends on availability of close substitutes for securities whose price could be affected by noise trading. Arbitrageurs who sell short overpriced securities have to buy same or similar securities that are not overpriced simultaneously in order to lay off their risks; however, securities do not have substitutes in many real cases. So, arbitrage could not help to pin down price levels of stocks and bonds as a whole.

In traditional finance models like CAPM and APT, arbitrage is realized by various tiny investors taking small positions. Whereas according to behavioral finance, arbitrage could only be realized by a small number of highly specialized investors (arbitrageurs) who combine their knowledge with other investors' resources. Shlefier and Vishny (1997) define limits to process of arbitrage under two headlines:

- Investors, whose money is managed by professionals (arbitrageurs), serve limited resources to arbitrage activity. They only care about losses and if losses take place, they refuse to provide more capital. They may even withdraw some of the capital. This contradicts with textbook arbitrage which requires no capital and entails no risk.

- People, whose money arbitrageurs manage, may enhance ability of arbitrageurs based on past performance and they determine amount of the capital they will invest based on that criterion.

Vaknin (2002) perceives economics as a branch of psychology. He criticizes traditional theories which assume economic actors to be in the rational pursuit of self-interest. He even conceptualizes “self-interest” as a tautology. He also criticizes their assumption which believes that individuals avoid repeating same mistakes while simultaneously they optimize their preferences. He also notes that individuals repeat same mistakes which are indicated by experimental evidences acquired in the area of behavioral finance. He finds preferences of people as inconsistent and attributes that to their tendency to put too much importance on near future relative to far future.

Shleifer (2000) also claims that investors’ deviations from economic rationality are pervasive and systematic. Deviations from standard decision making model are examined under three topics: attitudes toward risk, non-bayesian expectation formation and sensitivity of decision-making to framing of problems.

- Individuals do not assess risky gambles based on Neumann-Morgenstern rationality. They consider gains and losses relative to some reference point not at the levels of final wealth. They show loss aversion where loss function is steeper than gain function.

- Individuals violate Bayes Rule systematically. They tend to make predictions regarding future uncertain events by taking only a short history of data into account. By doing that, they generally ignore the possibility that recent history could be generated by chance.

- Choices individuals make differs depending on how problem is presented, namely framing affects decisions.

2.1. EXPECTED UTILITY THEORY

Bernoulli tries to explain human behavior in the case of uncertainty based on a measurable utility function. This is the simplest form of expected utility theory**.** (Abaan, 1998:125**)** Afterwards, John Von Neumann and Oscar Morgenstern (1944) develop Bernoulli's concept of expected utility and put it into a theory form.

Traditional finance theories like Efficient Market Hypothesis, CAPM, and Modern Portfolio Theory base on expected utility theory that is proposed by Von Neumann and Morgenstern (1944). They perceive expected utility theory as a normative theory that explains how participants in games of chance should behave. On contrary, in finance it is invoked as a positive theory explaining actual behaviors of individuals. (Bailey, 2005:93)

Expected utility theory begins with the assumption that all economic actors behave in a way that maximizes expected utility. It also includes a utility concept that could be quantified. According to that theory, a higher expected utility could be associated by a higher preference level.

Expected utility refers to value that is calculated by multiplying utility of each probable event with its probability. (Bostancı, 2003:3) Let's consider two cases, both causes result x to occur: Event a with probability p and event b with probability q,

If;

$$p.U(x)>Q.U(x) \qquad \textbf{(1)}$$

Namely if expected utility of event a, is higher than expected utility of event b, decision-maker will choose event a.

Expected utility theory bases on assumptions below;

- When people face with a case of uncertainty, they determine objective probability regarding realization of this case. In this determination, they use Bayes Theorem and they are assumed to have no bias.

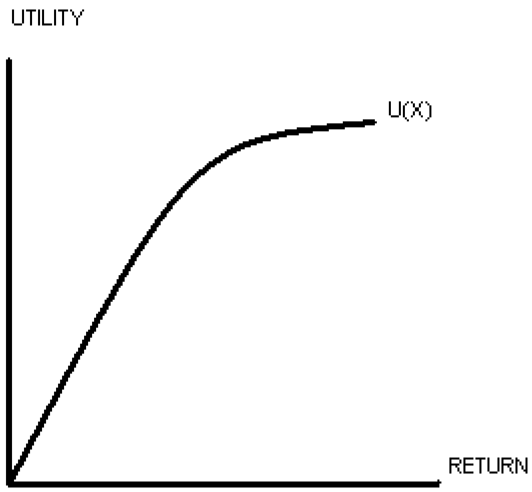
- If A provides higher utility than B, decision-maker will choose A from alternatives.

- Decisions people make, are assumed to be consistent with each other. If A provides higher utility than B and B provides higher utility than C; When A and C are the alternatives, decision-maker will prefer A. This is transitivity axiom.

- Dursun (1997) mentions that utility function bases fundamentally on diminishing marginal utility of money. According to Dursun, person who has no money could meet its requirements with $ 5000 he obtained. Nonetheless if he obtains a second $ 5000; this money provides him an additional utility clearly, but not as high as first $ 5000 provides.

Based on expected utility theory, utility function of a person is like the shape below;

Figure 3. Utility Function Of An Individual



(Bostanci, 2003, p. 4.)

Figure above expresses existence of a continuous relationship between return and utility. Moreover, it expresses that return increases are accompanied by utility increases. But, it is clear that utility increases in a diminishing way in consistence with rule of diminishing marginal utility.

Determinant structure of expected utility function bases on a hypothesis regarding human behavior. According to that hypothesis, people are risk averse. Namely, there is a relationship between diminishing marginal utility and risk aversion. People's attitude toward risk is determined by income level.

According to Bailey (2002), human behavior towards risk is expressed by utility function. He defines risk aversion as $U''(x) < 0$ (marginal utility of wealth is $u'(W)$, is decreasing) , risk neutrality as $U''(x)=0$ and risk loving as $U''(x) > 0$ (marginal utility of wealth is increasing). He adds that risk-loving and risk neutral attitudes toward risk are extreme forms of behaviors which are seldom observed.

Kahneman and Tversky (1979) explain expected utility theory based on three tenets.

$(x_1,p_1;......;x_n,p_n)$ is used to explain outcome x_i with probability p_i.

- "$U(x_1,p_1;......;x_n,p_n) = p_1u(x_1)+.......... +,p_nu(x_n)$ " . This expression is the overall utility of a prospect. This means that utility of a risky prospect is equal to expected utility of its outcomes, obtained by weighting the utility of each possible outcome by its probability. And when decision maker has to make a choice, he prefers the prospect that offers highest expected utility. (Kahneman and Tversky,1981:453)

However people make preferences that are incompatible with expected utility theory. Kahneman and Tversky develop prospect theory which modifies expected utility theory. Prospect theory tries to give answers to questions that are related with investor behavior which could not be answered by expected utility theory.

- A prospect is acceptable as long as utility obtained by integrating prospect with one's assets exceeds utility of these assets alone.

- In expected utility theory, concavity of utility function is thought to be equal to risk aversion. Risk-averse investor prefers certain prospect to any risky prospect.

However, Kahneman and Tversky (1979) claim that preferences of people violate these tenets.

2.2. PROSPECT THEORY

Expected utility theory, that is developed by Von Neumann and Morgenstern in 1944, is accepted as a normative model of rational choice and is tried to explain economic behaviors. It perceives that investors are always rational and risk averse. However, Kahneman and Tversky (1979) find expected utility theory inadequate and they have developed an alternative theory: Prospect Theory in which individuals are assumed to have limited rationality rather than full rationality in the case of uncertainty.

Shiller (1998) finds prospect theory similar to expected utility theory in which individuals maximizes a weighted sum of utilities, even though weights are not the same as probabilities and utilities are determined by value function, not the utility function.

In the same study; authors state that value function, which is defined on deviations from a reference point, is normally concave for gains and convex for losses. Concavity for gains entails risk aversion, whereas convexity of losses entails risk seeking. Sewell (2007) also associates concavity for gains with risk aversion, whereas he associates convexity with risk seeking behavior of people. He notes that value function is steeper for losses than gains which reflects loss aversion tendency of individuals.

Prospect theory asserts that people tend to give different weights to losses and profits in different probability levels. According to prospect theory, important risk is not the expected risk, but the perceived risk.

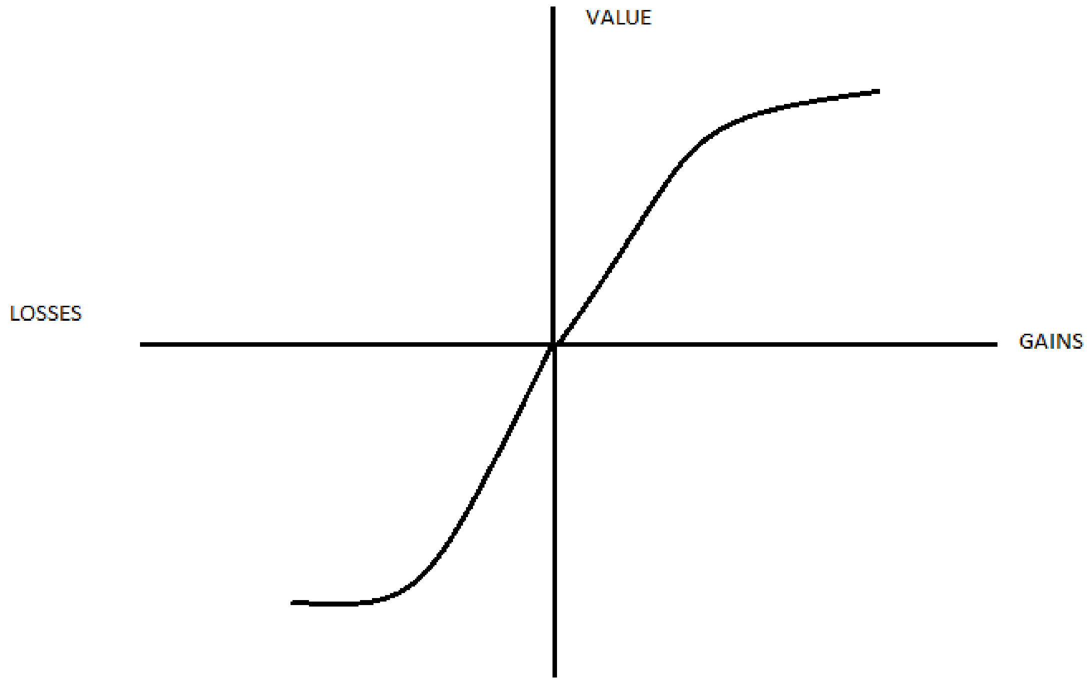
Foundations of Prospect Theory are: (Levy, 1992:174)

- People tend to think in terms of gains and losses rather than in terms of their net assets. As a result of this, they evaluate outcomes by deviations from a reference point rather than net asset levels.

- People's treatment to losses and gains are different. They are risk averse when gains are about issue, whereas they are risk acceptant when losses are about issue.

In expected utility theory, decision-makers are perceived to prefer the alternative that maximizes their wealth. In the decision analysis, outcomes of decisions are mentioned in terms of total wealth. However, Kahneman and Tversky (1984) find this view unrealistic from the psychological perspective. They assert that people normally think of relatively small outcomes; in terms of gains, losses and neutral outcomes; not in terms of states of wealth which is a foundation of prospect theory. (Like maintenance of status quo) Moreover, value function of prospect theory differs from utility function of expected utility theory in respect of "reference point which is the point of comparison against which alternative cases are compared" . Mentioned reference point is generally status quo point and have value of zero in theory. (Kahneman and Tversky, 1979:287) Shiller (1998) states that value function of prospect theory is concave downward for wealth levels above reference point and concave upward at levels below reference point. Kahneman and Tversky (1979) attribute this case to risk lover characteristic of individuals when losses are about issue.

Figure 4. S-Shaped Value Function



As it could be seen on the S-shaped graph, value function turns at the point of origin. Thaler (2000) also states that S-shaped value function is a basic finding in the psychology of perception which shows marginal sensitivity to both losses and gains. Bostancı (2003), explains that this due because people evaluate losses and gains in different ways. He states that disturbance that individuals felt due to small losses is higher than the pleasure that they felt due to gains. As an evidence of it, loss function is steeper than gain function. He also adds that as gains increase, marginal utility increases in a diminishing way. Similarly as losses increase, marginal disturbance will decrease gradually. Namely individuals tend to exhibit loss aversion in regions that is near to origin, whereas they exhibit loss seeking behavior as loss amount increases.

Kahneman and Tversky (1992) note that disturbance that is felt by individuals due to probable losses is approximately twice as larger as the pleasure they feel due to possible gains. Levy (1992) examples that phenomenon with saying of Jimmy

Conners who says "I hate to lose more than I like to win." Kahneman and Tversky (1992) conclude that loss aversion determines the preferences of people. Thaler (2000) also mentions that losses hurt about twice as much as gains make people feel good.

2.3. HEURISTICS

In early England, carpenters assume that upper part of their thumbs is 1 inch and they make calculations based on that assumption. This is a way to reach the result by approximate calculations but findings obtained by this way are not certain. This is only a way to reduce complexity of analyzing information; other way to reduce complexity is using heuristics. Döm (2003) states that heuristics help brain to organize huge amount of information. Despite easiness of usage of heuristics, they make analysis of new information more complicated and they may even cause people to make inaccurate decisions.

Aronson (1992) points out cases which will cause individuals to use heuristics as:

-When individual is over-loaded with information, it becomes harder to process information,
- When there is not enough time to consider on a subject,
-When individual does not want to consider on events that depends on chance,
-When individual has little information regarding subject on which decision is made.

According to Tversky and Kahneman (1974), people rely on a number of heuristic principles that decrease complexity of tasks of assessing probabilities and predicting values. Authors also point out that despite usefulness of these heuristics, they could also lead to systematic errors. According to authors, there are three types of heuristics that cause cognitive biases. These are representativeness heuristics, availability heuristics and adjustment and anchoring.

2.3.1. Representativeness Heuristics

Based on law of large numbers of the statistics; it is required for a sample to be sufficiently large enough to represent population. However, based on law of small numbers of psychology, people tend to make judgments without considering sample size. Kahneman and Tversky (1974) illustrate it with an example. In an experiment, it is explained that an individual is selected randomly from 100 professionals. In the first condition, participants are told that group consists of 70 engineers and 30 lawyers; in the second condition they are said that there are 30 engineers and 70 lawyers. Authors conclude that possibility that description belongs to an engineer rather than to a lawyer should be higher in the first condition, where there is a majority of engineers than in the second condition, where there is a majority of lawyers. (Tversky and Kahneman, 1972:1124) However participants estimate same probability judgments for both conditions, by violating Bayes' Rule. As a conclusion; authors note that with no regard to prior probabilities of categories, participants judge the likelihood that description belongs to an engineer rather than a lawyer only by considering degree to which description was representative of stereotypes. This case in which people create opinions without considering sample size, which is an implication of law of small numbers, leads scientists to exaggerate confidence in the validity of conclusions inferred based on small numbers.

Shefrin (2005) states that representative heuristics refers to tendency of people to rely too much on stereotypes. Because of representative heuristics, investors might misattribute good characteristics of a company as characteristics of a good investment. However Lakonishok et al (1994) indicate that these glamour companies are generally poor investments. Similarly, investors may inaccurately perceive recent returns as representative of future returns. This misperception may cause investor to buy stocks that have recently increased in price.

Ritter (2003) states that people tend to overweight recent experience. Shleifer (2000) criticizes that tendency of people by saying that recent history could be generated by chance. Additionally, Ritter adds that long-term averages are tended to be underweight. He calls these tendencies "law of small numbers". As an example he gives that; after high equity returns that have continued for many years, people may start to perceive these high returns as normal.

Benartzi (2001) suggests that employees may perceive abnormally high past performance as a representative of future performance, despite unpredictability of stock returns. Namely, they may extrapolate past performance. With this perception, employees may invest their retirement savings into stocks of company they work for.

Pompian (2006) who perceives representative heuristics as a cognitive bias examined under it under two headlines:

- **Base-Rate Neglect:** In that neglect, investors attempt to determine potential success of an investment in Company A by putting venture into a more familiar classification. This investor categorize venture and draw conclusions regarding risks and rewards from that classification. This logic may cause other variables, which could impact success of investment, to be ignored.

- **Sample-Size Neglect:** In this neglect investors fail to consider sample size of data on which they base their judgments. They incorrectly perceive small samples as representatives of populations .Some authors call this phenomenon “law of small numbers”.

Use of representative heuristics in financial area may direct investors to make serious errors. For instance, some investors may put too much emphasize on short past histories of rapid earnings growth of some companies and assume this growth to carry on. Such overemphasizing may cause these companies’ stocks to be overpriced. According to Shleifer (2000); since it is not possible for these companies to maintain such high growth rates, such overreaction lowers future returns.

2.3.2. Availability Heuristics

People often search their memories for relevant information when judging the probability of an event. At the end of this process, biased estimates may be produced since all memories are not equally available. Kahneman and Tversky

(1974) define availability heuristic as the situations in which people associate frequency of a class or probability of an event by the ease which instances can be brought into mind.

Although availability heuristic constitutes a useful clue for assessing frequency or probability, sometimes it could cause serious errors. Based on Döm (2003), people have much confidence to ideas based on recent information and they tend to give much importance on concrete information than statistical information. Barberis and Thaler (2002) also note that people will overweight more recent and more salient events. If any thing is easily remembered, people perceive it as frequent. Kahneman and Tversky (1974) state that impact of seeing a burning house is greater than impact of reading it on newspaper. Seeing it will cause individual to remember it more easily which is called salience bias. Similarly, biased media news that encourages attentional bias could change judgments. In a study conducted, it is seen that death causes which are statistically frequent are neglected in the newspaper news whereas catastrophic events like tornadoes, fires, drownings, homicides and accidents were reported disproportionately often. Despite illnesses take 100 times as many lives as do homicides, there are about three times as many articles about homicides as about diseases. (Slovic et al., 1980:185)

Pompian (2006) defines availability heuristic as a mental short cut that allows people to estimate probability of an outcome based on how familiar that outcome appears in their life. (Pompian, 2006:94) Moreover, people assume readily available thoughts, ideas, and images to be indicators of statistical probabilities. They associate likelihoods of events with degree of ease with which events can be accessed from memory. Availability heuristic can be categorized under four topics:

- **Retrievability:** Pompian (2006) notes that a class whose instances are easily retrieved will appear more credible than a class of equal frequency whose instances are less retrievable, although this is not the case. Kahneman et al (1974) make an experiment in which participants are read list of names including names of male celebrities and then asked if more female or male names are read. In reality, more female names are read; however with the effect of male celebrities’ names, participants estimate that males dominate the list. This is a result of availability heuristics.

- **Categorization:** Availability heuristic emphasizes how people attempt to summarize information. Investors have a tendency to invest in stocks whose categorization they make on their brain and they most likely neglect the stocks that they have not categorized yet.

- **Narrow Range of Experience:** If individuals who want to make estimations regarding future have a narrow range of experience, their probability to make wrong estimation is high. Same thing is valid for investors. Investors with narrow range of experience will more likely to make wrong estimations and because of that reason they may involve in wrong investments.

- **Resonance:** Individuals have a tendency to perceive individuals, who share same ideas and interests with them, more frequent. According to Pompian (2006), classical music listeners overestimate the population who listen classical music, on contrary the ones who hate from classical music underestimate population who listen classical music. Similarly, investors will interest in investment opportunities that suit their habits and behaviors and they will ignore other opportunities even if these opportunities are more profitable. Investors investing in Islamic banks could be given as an example.

2.3.3. Anchoring and Adjustment Heuristic

Kahneman and Tversky (1974) state that people make estimations by starting from an initial value (the anchor), which will be adjusted to yield final answer. Initial value either could be suggested by formulation of the problem, or it could be result of a partial computation. Authors note that in both cases adjustments are not sufficient. In other words when people attempt to make estimations, they generally start estimation with an initial value (the anchor). This anchor could be defined as a reference point. As new information acquired, people make adjustments that are insufficient to this reference point.

Values in speculative markets, like stock markets, are ambiguous. According to Shiller (1999), there is not an economic theory that could answer what value of Dow Jones Industrial Average should be. In such cases people need a reference point based on which they evaluate changes while making judgments. Shiller (1999) also states that past prices are important determinants of current prices if better information does not exist.

In certain forms of money illusion, which refers to tendency of human to make inadequate allowance in economic decisions for inflation rate and their tendency to confuse real and nominal quantities, anchoring could be behind.

Shafir et al (1997), mention from the answers of people to same decision problem, which change according to framing, if problem is presented in nominal quantities or real quantities. Quantities that are either represented in nominal or real form could be functioned as anchors. (Shiller, 1998:10)

Pompian (2006) suggests that investors should ask themselves a question to avoid being affected from anchoring and adjustment bias. This question is "Is my estimate rational or am I anchored to last year's performance figures?" Author states that some finance professionals could leverage anchoring and adjustment bias. To do it, they observe patterns in securities analyst's earnings upgrades (downgrades) on some stocks and purchasing (selling) them in response. By following this strategy investor takes advantage of tendency of analysts to underestimate.

2.4. COGNITIVE BIASES

Human brain works as a computer and process information by using some heuristics and emotions. Decisions individuals make with the effect of emotions generally differ from decisions they make based on logic. Mentioned deviations from rationality that individuals show are defined as cognitive anomalies. It is proved that these cognitive biases are independent from IQ or education level.

Cognitive biases have been examined under several topics in finance literature. Here, they will be examined under eight topics:

- Overconfidence,
- Confirmation bias,
- Hindsight bias,
- Cognitive dissonance bias,
- Conservatism Bias,
- Ambiguity Aversion Bias,
- Optimism bias,
- Primacy, Recency and Dilution Effect

2.4.1. Overconfidence

As it will be examined in detail, overconfidence refers tendency of people to overestimate precision of their beliefs, forecasts and abilities. (Bodie et all, 2009: 386) Pompian (2006) defines overconfidence as unwarranted faith in one’s intuitive reasoning, judgments and cognitive abilities. (Pompian, 2006: 51)

In financial markets, analysts generate information via interviewing management, verifying rumors, analyzing financial tables. According to Daniel, Hirshleifer and Subrahmanyam (1998), overconfident investors overestimate precision of their knowledge about value of a financial security. They make definition of an overconfident investor as the one who overestimates precision of his private information signal, but not signals that are received by public. In consistence with that overconfident investors tend to neglect publicly available information, whereas they tend to pay attention to rumors. When they overestimate their abilities, they will generally underestimate their forecast errors. Even they are not sure about accuracy of information, they believe that information on their hand is sufficient to process and make decision.

Individuals will be more overconfident, as they believe that they could control the results that will be obtained. Tendency of investors to be more overconfident is more intense, when success is obtained at the beginning of a work. Individuals with recent successes are also more inclined to be overconfident.

Because of these reasons investors could make more active and speculative decisions.

Overconfidence affects attitudes of individuals toward risk. Generally overconfident investors evaluate risk level they take on inaccurately. This is the case, since perceived risk is more important than expected risk for them. Overconfidence causes investors to expect high returns. Overconfidence leads investors to hold undiversified portfolios and taking on more risk without a commensurate change in risk tolerance. (Pompian, 2006:54) They make too little diversification due to their tendency to invest too much in what they are familiar with. Because of that tendency, they are inclined to invest in local companies and companies they work for. (Ritter ,2003 :4) Overconfident investors also underestimate downside risks which will cause poor portfolio performance, since they do not pay attention to historical investment performance.

Rational investors trade and purchase information; only when doing so increases their expected utility. On contrary, overconfident investors decrease their expected utility by trading too much. They make excessive trades because of the belief they hold regarding they have special information that others do not have. Those excessive trades lead to low returns over time.

Deviations from efficient market theory may be explained by behavioral biases. One of those biases is overconfidence. Overconfidence assumes individuals to have unlimited ability in observing and processing information. However, in reality individuals have limited ability in processing information and they can be affected by behavioral biases.

It is stated that the most robust finding in the psychology of judgment is overconfidence. (Debondt and Thaler, 1995: 389) According to Griffin and Tversky (1992), experts are more inclined to be overconfident compared to inexperienced ones. Overconfidence is also stronger for tasks for which feedback is slow like diagnosing illnesses relative to tasks for which feedback is immediate like weather forecasting.

Daniel and Titman (1999) find self-confident individuals more competent than insecure individuals. They conclude that in theory, individuals who filter information in a way that contributes their self-confidence could be more successful than individuals who rationally interpret information.

More information about overconfidence will be provided at the third section of the study.

Three reasons are emphasized that are thought to increase overconfidence. These are self-attribution bias, illusion of knowledge and illusion of control. (Döm, 2003:62)

2.4.1.1. Self-attribution Bias

Pompian (2006) defines self-attribution bias as individuals' tendency to ascribe their successes to innate aspects like talent or foresight, while more often blaming failures on outside influences like bad luck. We could give an example showing that bias. According to Shefrin (2000), having a financial consultant is similar to having a buy option. If results of investment are positive, investor will attribute them into his own talents. But if results are negative, he will attribute failure to consultant. By this way, he will reduce his regret and satisfy his ego.

Jongersen (2003) defines overconfidence as initial overreaction of prices to private information. According to same author, biased self attribution refers to new information that supports investors' private information which is weighted more than contradictory news.

Pompian (2006) examines self-attribution bias under two headlines:

-**Self-Enhancing Bias:** refers to individuals' propensity to give too much credit for their successes.
-**Self-Protecting Bias:** refers to denial of responsibility for failure and tendency to find reasons for failure.

People tend to attribute not only real successes, but also the ones that are led by chance to them. Particularly, it is easier to get higher returns in an increasing bull market. In a bull market, many investors start to make investments. If these new investors attribute success to only themselves, serious problems will be faced. (Döm, 2003:62)

In most cases, investors with self-attribution bias take too much risk and become overconfident. They are also inclined to make too many transactions. That bias lead investors to hold undiversified portfolios. This is the case, especially when corporate executives or board members attribute success of the company only to their own contribution.

2.4.1.2. Illusion of Knowledge

Individuals tend to think that accuracy of their estimations will increase, as they have much information. This is generally accurate, but not always it is the case. Nofsinger (2001) explains three reasons of why this rule is not always accurate as:

-Some information does not help investors to make estimations; it even directs investors to wrong way.
-Most people do not have enough education level, experience and talent to evaluate this information.
-People are inclined to evaluate new information in a way that will verify their existing beliefs and ideas.

2.4.1.3. Illusion of Control

Illusion of control can be described as tendency of human to believe that they could control or at least influence outcomes, when in fact they can not**. (**Pompian, 2006:111) Another definition is made by Ellen Langer, who works in psychology department of Harvard University as "expectancy of a personal success probability that is inappropriately higher than the objective probability would warrant."

2.4.2. Confirmation Bias

Various studies indicate that after forming strong hypotheses, people tend to be more inattentive to new information that contradicts with their existing hypothesis. (Rabin, 1998:26) Rabin qualifies that bias as a demonstration of anchoring.

Investors overweight and collect the information supporting their own beliefs and tend to extract information that contradicts with their beliefs. This tendency is called confirmation bias.

Lord et al (1979) also asserts that people having strong opinions on complex social issues, are more likely to process empirical evidence in a biased manner. They accept confirming evidence, but expose disconfirming evidence to critical evaluation. Authors mention that people tend to evaluate subsequent evidence in a way so as to maintain their initial beliefs. In this biased assimilation process, people tend to remember strengths of confirming evidence and weaknesses of disconfirming evidence. By this way complexity of information decreased, and only a few supportive impressions are remembered. Namely, by doing so data is processed in a biased fashion in order to maintain initial preconceptions of people.

Lord et all (1979) make a questionnaire which includes three questions regarding capital punishment to 151 undergraduates. A few weeks later from the first questionnaire, 48 of these students are involved in another experiment. From them, 24 students are initially proponents favoring capital punishment and believed that it has a deterrent effect. Other 24 students are initially opponents who are opposing capital punishment and not believe in its deterrent effect. Surprisingly, both groups suppose that relevant research supports their views.

After then, participants are asked to read some studies about deterrent efficacy of death penalty and are also asked to evaluate if given study provides evidence for or against deterrence hypothesis. After then they answer 2 sets of questions on 16 point scales. By this way, it is tried to be measured how studies they have read changed their attitudes toward capital punishment (-8 =more opposed to capital punishment +8=more in favor) and their beliefs about deterrent efficacy of death penalty. (-8=less belief that capital punishment has deterrent effect,+8=more belief to its deterrent effect) As a conclusion authors find that proponents of death penalty become more in favor of the death penalty and excessively believe in its deterrent efficacy, whereas opponents become less favor of death penalty and less believe in its deterrent efficacy. (Rabin, 1998:27) This is an illustration showing that same ambiguous information may cause beliefs of people who holds different initial beliefs to become further apart.

With the effect of confirmation bias, people ignore or at least underweight information that lowers their self-esteem. For instance, people are reluctant to sell their losers since it requires them to admit that they have made a mistake which will cause their confidence to reduce. Similarly, investors tend to overweight information that supports their earlier decisions. They also filter out information suggesting that their earlier decisions were mistakes. (Daniel and Titman, 1999:29)

2.4.3. Hindsight Bias

Hindsight Bias is the tendency of people, with the benefit of hindsight following an event, to falsely believe that they predicted the outcome of that event in the beginning. (Pompian, 2006:200) This tendency which is called hindsight bias by Fischoff (1975), also called I knew-it-all-along effect.

Hindsight bias is firstly proposed by Baruch Fischoff in the study he conducted in 1975. He explains that bias by observing

- Perceived probability of an outcome's occurrence increases, as reporting regarding occurrence of that outcome increases.
- People, who receive knowledge about outcome, are unaware of the fact that their perception have changed.

When these two factors come together, hindsight bias comes into being and people tend to exaggerate the quality of their initial knowledge. Moreover, they tend to forget their initial errors.

After an event takes place, people are inclined to perceive that the event was predictable- even if it was not. After a politician wins election, people label it as if it was inevitable and believe that they have always believed that it is inevitable. (Rabin, 1998 :30) With the effect of same bias, many experts make confident explanations regarding why market behaves in that way to public every day after stock market closed.

With reference to Kahneman and Riepe (1998), hindsight errors are pernicious in two ways:

- Since hindsight bias fosters the illusion that shows world more predictable than it is, it tends to increase overconfidence.

- Authors define this bias as a lesson that financial advisors learn painfully. Hindsight bias turns reasonable gambles into foolish mistakes in the minds of investors. After a stock decrease in value, its fall is perceived as inevitable. But if this is the case, why has not advisor advised investor to sell it before?

2.4.4. Cognitive Dissonance

Shiller (1998**)** defines cognitive dissonance as a mental conflict, which people experience when they are presented evidence showing that their beliefs or assumptions are wrong; it might be also classified as a type of pain of regret that is felt over mistaken beliefs.

When new information is in contradiction with existing understandings, people feel a mental discomfort called cognitive dissonance. It could also be defined as the case in which individuals' beliefs and information contradicts with each other or behavioral tendency. In the case of cognitive dissonance, people try to get rid of discomfort. They do this by reducing importance of contradicting beliefs and increasing importance of beliefs that are in harmony. Namely when cognitive dissonance takes place, people modify their behaviors and cognitions to reduce the feeling of discomfort it faces with. (Barak, 2008:115)

Festinger (1957) asserts that there are three ways to eliminate or at least reduce dissonance:

-Changing Cognitions: If two cognitions contradict with each other, one of the cognitions could be changed in a way that provides harmony between cognitions.

-Adding Cognitions: If two cognitions lead to a considerable size of contradiction, size of contradiction could be reduced by adding a few cognitions that are in harmony.

-Altering Importance: To reduce contradiction, importance of beliefs that are in harmony can be increased**.**

If an investment begins losing after an investor invests in it, investor falls into an emotional discomfort and try to justify that decision he has made was accurate. He falls into discomfort, since losses he faces contradict with some cognitions of investor. These cognitions are like "I am a skillful and successful investor" or "I invest only to make profit." Because investor will try to justify decisions he has made, he will create new cognitions to rationalize his decision. These new cognitions are like "My investment will appreciate in the future" or "Loss I face with is temporary." By this way, by eliminating contradicting cognitions, cognitive dissonance will be eliminated.

2.4.5. Conservatism

Conservatism bias is a mental process, in which people cling to their prior views or forecasts at the expense of acknowledging new information. (Pompian, 2006:119) Barberis et al (1998) evaluate conservatism bias as the state, in which individuals are slow to change their beliefs despite appearance of new evidence. It could be said that they anchor on the ways things have normally been.

Conservatism bias leads investors to under react new information, this is the way because of the fact that investors try to maintain their initial estimates or beliefs. Conservatism bias seems to conflict with representativeness bias; according to which people overreact to new information. However, people may exhibit both biases. If new information is a representative of an underlying model, in accordance with representativeness bias people overweight data. However, if representative relationship does not exist, conservatism bias dominates and new data is underemphasized. People continue to rely too much on their prior beliefs.

Edwards (1968) proves that individuals update their initial beliefs in the right direction, but by too little in magnitude compared to a rational Bayesian. In his own words:

"*It turns out that opinion change is very orderly and usually proportional to numbers calculated from the Bayes Theorem - but it is insufficient in amount.*"

An investor, who is subject to conservatism bias, may disregard new negative information that could affect the value of stock which he invests in; he may reject to change his investment strategy based on new information. Think of an investor who has purchased a security, based on knowledge that company is planning to make announcement of a new product. Then company announces that they have problems regarding launch of new product. In spite of new negative information, investor may still cling to initial positive information and may ignore the second negative one. This case could be attributed to mental stress investors experience when they face with complex data.

According to Barberis et al (1998), individuals who are subject to conservatism bias may disregard information of earnings announcement. When conservatism biased investors react to new information; they do this too slowly. Because of that reason if earnings announcements cause stock to depress, its holder may be too slow to sell it. Investor tends to sell the stock only after losing too much money.

2.4.6. Ambiguity Aversion Bias

Ambiguity Aversion Bias refers to situation where people do not like to gamble, when probability distributions seem uncertain. (Pompian, 2006: 129)

Tendency of individuals to hesitate in the cases of ambiguity called ambiguity aversion bias.

Knight (1921) is the first one who has mentioned from ambiguity aversion bias. He defines "risk" as a gamble with a precise probability distribution. According to him, "uncertainty" materializes when distribution of possible outcomes resulting from a gamble could not be known. He also concludes that people dislike uncertainty more than they dislike risk. (Pompian, 2006:129)

People try to avoid uncertainty. Financial markets are full of ambiguity and because of that reason; they are hard to understand for many people. It is not possible to estimate value of ISE-100 index for six months later certainly. Bostancı (2003) asserts that ambiguity aversion could be an explanation for equity premium puzzle. Investors find stock market ambiguous and they demand higher premium to involve in it. Since investors demand higher premiums for risks of investing in certain assets due to ambiguity aversion, they hold only conservative investment instruments.

Modern portfolio theories suggest that investments should be distributed to different countries. By this way, risk could be diversified away. Nonetheless, this is not the case in real world. With the effect of that bias, people are inclined to invest only in their national indexes in real world. They invest in their national index because of its familiarity. Namely, ambiguity aversion could be said to explain home bias. French and Poterba (1991) find that investors of USA, Japan, England make %94,%98,%82 of their investments to stocks of their home country respectively. Bostancı (2003) also concludes that people prefer national index stocks to foreign stocks, companies in their region to the ones in other regions. Moreover, he notes that people prefer familiar and simple investment instruments. By this way, they constitute less efficient portfolios and even it could be said that they could not exploit arbitrage opportunities offered.

Similarly, Benartzi (2001) notes that individuals tend to construct portfolios that are highly concentrated on stocks of company they work for. Individuals do this since they perceive their employer's stock as safe and other stocks as ambiguous. Particularly, when employers automatically direct their contributions to company stock, employees increase the amount they invest in company. It could be said that they evaluate employer's contributions as investment advice.

2.4.7. Optimism Bias

Optimism bias is a cognitive bias that causes people to trust their information unnecessarily, exaggerate their talents to control events and underestimate risks involved in. Kahneman and Riepe (1998) state that % 80 of drivers qualify themselves as above-average. Authors criticize that case , by saying most of them must be mistaken.

Optimism bias, directs individuals to underestimate the likelihood of bad outcomes over which they have no control. Namely, optimism biased individuals are also prone to illusion of control. They exaggerate degree of control they have over events and they tend to discount the role of chance. Optimism bias causes investors to invest in near geographic region, due to the fact that they are optimistic about prospect of near geographic area. (Pompian, 2006:167)

Optimism bias defines tendency of people to wear "rose-colored glasses". People who wear them view the world with an excessive optimism. Optimism biased investors tend to be too optimistic about market, economy and outcomes of the investments they have made. Most of the optimistic investors believe that they will be not affected from bad investments. Such wrong oversights of optimistic investors make their portfolios more exposure to damages.

2.4.8. Primacy, Recency and Dilution Effect

Primacy Effect is the tendency of individuals, to recall and emphasize information that is acquired in the past rather than recent information.

Recency Effect, is just the opposite of primacy effect. It is a cognitive bias that causes people to remember and emphasize recent information rather than past information. It is said that recency effect is more frequently seen compared to primacy effect. (Döm, 2003:87) Recency effect could be observed during evaluation of performance of a portfolio manager. People are inclined to measure performance of a portfolio manager, with its recent success or failure rather than its cumulative performance.

Investors, who are affected from recency effect, are more inclined to purchase assets at price peaks; since they forecast future returns based only on a recent sample of prior returns. By this way, assets may become overvalued. Furthermore, recency bias may cause investors to disregard fundamental value and concentrate only on recent price performance.

Dilution Effect, is the tendency of neutral or irrelevant information to influence judgments in an unduly way. Sometimes irrelevant information and ideas reduce attractiveness of an investment instrument and cause investors to invest in wrong investment instruments. Also; information that is overloaded, may lead investors to pay attention to ways of information that are unnecessary. This means that judgments are affected not only by order of the information but also amount of information. (Barak, 2008: 111)

2.5. EMOTIONAL BIASES

Not only cognitive biases, but also emotional biases affect the investor behavior. Nevertheless it is more difficult to show effect of emotional biases on investor behavior, compared to effects of cognitive biases since emotions are hard to measure. (Barak, 2008:114)

In this section, emotional biases which affect investor behavior will be examined. These biases are:

-Endowment Effect and Statu Quo Bias
-Self-Control Bias
-Regret Aversion
-Disposition Effect
-Hedonic Editing

2.5.1. Endowment Effect and Status Quo Bias

People tend to value things what they possess, more than "comparable” things they do not possess. This over-evaluation of current possessions has been called endowment effect. (Thaler, 1980, pp. 43-47)

Experiments that are made indicate that people have a great tendency to continue their status-quos. Barak (2008) explains that disadvantage of giving up status quos is more important than its advantage. Difference between buying price and sales price is also attributed to this. In the case of a sale, seller perceive sales process as intrude to its current status and to compensate that disturbance he tends to demand much more to sell the object than he would pay to purchase it. Kahneman et al (1991) also identify preference for current state, as an indicator of status quo bias. They also evaluate endowment effect and status quo bias as a manifestation of loss aversion which implies that disutility of giving up an object is greater than the utility of acquiring it.(Kahneman et al,1991:194)

Parallel to explanations above, loss aversion and the endowment effect together imply that selling prices should be higher than buying prices: the minimal compensation people demand to give up a good is often several times larger than the maximum amount they are willing to pay for a commensurate entitlement. (Levy, 1992:175)

Based on Barak (2008), people evaluate losses and gains in different ways. Loss aversion is a type of behavior that appears as a result of individuals’ tendency to overweight losses and disadvantages, compared to gains and advantages. As mentioned before, effect of losses on people is higher than effect of gains. This is the case because in the case of losses, there is a loss from current state. However in the case of gains, gain that has not gained yet is the one that is about to decrease. Namely in the first case a decrease in standards is felt by individuals, but in the second case they lose the one that they have not earned yet.

Another illustration of endowment effect is given by Knetsch and Sinden. (1984:510-511) In this example, participants are offered either a lottery ticket or $ 2.

After some time, same participants are given opportunity to trade ticket for money or save the ticket. And it is observed that only few participants switch ticket to money. As it could be understood from this example, endowment effect could cause people to save objects that could decrease in terms of value. That effect is said to be balanced by loss aversion in some respect.

2.5.2. Self-Control Bias

Self-Control Bias is the tendency of people to consume today at the expense of saving for tomorrow. (Pompian, 2006: 150) It refers to dilemma people face, between satisfaction of short term returns and long term returns.

Self-control bias could be explained under the context of life-cycle hypothesis. Model describes tendencies of individuals, to divide income into consumption and saving. Saving decision of present represents individual's preference over present versus future consumption. Most individuals start with lower incomes at early working years. Their incomes increase and reach to peak near retirement. Income during retirement is lower when pensions are taken into account. People may make up lower income of retirement with the savings they made during working years.

With reference to life-cycle hypothesis;

-People mostly prefer a higher standard of living to lower standard of living.
-People try to maintain a constant standard of living during their lives. They do not like volatility.

Namely, life-cycle hypothesis states that people try to maintain a smooth and high consumption path.

Self control bias, leads investors to spend more at the expense of saving for tomorrow. This case will be hazardous for people who have not made enough savings. Moreover, asset allocation imbalance problems may take place because of self control bias. Investors with self control bias might prefer income- producing assets with the effect of spend today mentality. That preference may damage long-term wealth since income-producing assets may prevent a portfolio to keep up with inflation.

Bostancı (2003) asserts that even if Homo Sapiens know the best preference, due to fact that it could not control itself, it may not prefer it. Even if people know that smoking and overeating damages to health, they do it. Similarly, investors may prefer risky stocks with the effect of self-control bias to increase their short term returns.

2.5.3. Regret Aversion

Regret theory is said to be firstly formulated by Bell (1982) who concludes that by adding regret into utility function, individual behavior could be better explained. Author also mentions from a need for further investigation of the role of regret in decision-making.

Impact of regret on decision-making has been examined for different scenarios and by various authors:

- Braun and Muermann (2004) examine for demand for insurance,
- Muermann et al (2006) examine for portfolio choice ,
- Michenaud and Solnik (2006) examine for currency hedging ,
- Filiz and Özbay examine for first price auctions

Shefrin and Statman (1985) define regret as a feeling that is associated with ex post knowledge that a different past decision would have fared better than the chosen alternative**.** This means that individual's ex-post level of wealth could be higher if he had made the alternative decision.

Pride is the positive counterpart of the regret. It is an ex-post feeling that ex-ante decision turned out to be better than the disregarded alternative decision. (Muermann and Volkman, 2007:5) Selling a stock at a loss leads investor to feel regret, whereas selling it with gain induces pride. Shefrin and Statman (1985) assert that pursuit of pride and struggle for avoiding regret, create disposition effect which leads investors to realize gains and defer losses.

Individuals feel regret when a stock that is considered to be bought but then given up appreciates. Individuals try to rationalize this case in order not to feel regret. Barak (2008) addressed the study of Shefrin (2000),who have concluded that investors who manage their investments by their individual decisions feel regret more intensely than other investors managing their portfolio with the help of a consultant. They point out the decision-making that is made by themselves as a reason for this. (Barak, 2008:118)

Regret aversion may cause investors to hold too conservative investment strategies. They are inclined to accept only low-risk positions which could result in an underperformance in the long term. Moreover, regret aversion may cause investors to avoid from markets that have recently gone down. Individuals who are subject to regret aversion fear from investing in such a market, since downward trend of market may continue. Nonetheless, such depressed markets usually offer bargains. (Pompian, 2006: 231)

Regret aversion leads investors to hold not only winning stocks, but also losing stocks too long. In the case of losing stock, they are reluctant to admit that they have made a mistake and continue to hold losing stock. On the other hand, in the case of winning stock investors avoid selling it; since they fear that stock may increase further which could cause them to feel regret.

2.5.4. Disposition Effect

Disposition Effect**,** which is firstly proposed by Shefrin and Statman (1985), is defined as a positive theory of capital gain and loss realization based on which investors are inclined to sell winners too early and ride losers too long. Statman, Thorley and Vorkink (2006) comment that Shefrin and Statman (1985) combine prospect theory of Kahneman and Tversky with emotions of pride and regret. Both Barber and Odean (1999) and Chen et al (2007) also mention that disposition effect is one implication of extending prospect theory to investment decision making. Under prospect theory, people behave as if they are maximizing S-shaped value function that is similar to standard utility function. Shefrin and Statman (1985) examine disposition effect from the perspective of prospect theory, mental accounting, loss aversion and regret. From the perspective of prospect theory, it is stated that an investor purchased a stock from $ 50 which is now selling for only $40. After then two alternatives were shown from which investor is expected to make a choice. First alternative is, selling stock and realizing $ 10 paper loss. Second alternative is, holding stock for one more period in which two outcomes possible, losing an additional $10 or breaking even. Authors conclude that since choice between alternatives is associated with convex portion of S-shaped value function, second is expected to be preferred over the first. Namely, losing stocks will be hold. From the mental accounting perspective decision makers divide different types of gambles that are faced into separate accounts. After then they disregard the interaction between them and apply prospect theoretic decision rules to each account. Shefrin and Statman (1985) state that Gross (1982) describes many features that illustrates mental accounting. They use quotation of Gross which mentions from difficulty of loss realization. Gross suggests in his own words;

"*Many clients, however, will not sell anything at a loss. They don't want to give up the hope of making money on a particular investment, or perhaps they want to get even before they get out. The "getevenitis" disease has probably wrought more destruction on investment portfolios than anything else. Rather than recovering to an original entry price, many investments plunge sickengly to even deeper losses. Investors are also reluctant to accept and realize losses because the very act of doing so proves that their first judgment was wrong ...*"

In the finance literature investors tend to sell stocks with good performance by this way to feel themselves good. On contrary, they are reluctant to sell stocks with poor performance because this requires them to accept that they have made a mistake and they afraid that stock may recover. Statman, Thorley and Vorkink (2006) make same implication by saying in their own words :

" *Pride accompanies the realization of paper gains, and regret accompanies the realization of paper losses.* "

Feelings of regret and pride are shown as explanations for disposition effect by Shefrin and Statman (1985). Muerman and Volkman (2007) explain the idea that lies behind disposition effect as; an investor will hold a losing stock due to fact that he hopes it will rise in the subsequent period, namely it tries to avoid regret. If the stock he holds rises, investor tends to sell the stock to feel pride. Namely, investor tries to prevent the feeling of regret that could take place if the stock he holds falls. Muermann and Volkman (2007) conclude that investors realize gains more rapidly than losses since they want to feel pride and defer regret.

Individuals are risk averse in the area of gains and risk-seeker in the area of losses. Due the fact that winning stocks can be considered as a gain, individuals are risk averse in this domain and they sell the stock. On contrary since losing stock is considered as a loss, individuals will be risk seeker in this domain and continue to hold the stock. This shows how loss aversion explains disposition effect. Barber and Odean (1999) conclude that loss aversion explains disposition effect in the best way.

Shefrin and Statman (1985) mention that investors tend to sell losers in December. Authors postulate that, this tendency is a result of self control strategy. They comment that investors sell their losers in December to recognize tax benefits. On the contrary, Lakonishok and Smidt (1986) conclude that disposition effect is more dominant than tax-related motives for selling stocks at a loss.

Dhar and Zu (2006) note that disposition effect is stronger for investors with less trading experience.

2.5.5. Hedonic Editing

Hedonic Editing is the process of integrating existing results with preceding results and evaluating their sum in stead of evaluating each result separately**.** Aim of the hedonic editing is the value maximization. Thaler and Johnson (1990) state that rules for hedonic editing follow four principles:

- Segregate gains
- Integrate losses

- Segregate small gains from larger losses (The "silver lining" principle)
- Integrate (cancel) smaller losses with larger gains.

These principles are applied whenever possible based on hedonic editing hypothesis. (Thaler and Johnson, 1990: 647)

Decision makers are more likely to accept risky gambles, after gains realized. This effect is called house money effect. On contrary their willingness to take risk decreases, after losses they faced. Also, after prior losses outcomes that offer to “breakeven” are also found attractive by investors. (Thaler and Johnson, 1990:644) Based on quasi-hedonic editing hypothesis, prior losses may be followed by risk aversion. Losses that take place after a gain and smaller than the original gain may be associated with prior gain. Moreover those losses may reduce the effect of loss aversion and may facilitate risk-seeking. Phrase of gamblers “playing with the house money” is the idea that takes place behind this effect. It expresses that investors, like gamblers, code loses as reductions from gain until the time that past winnings are completely depleted.

2.6. MENTAL ACCOUNTING

Before definition of mental accounting, Thaler (1999a) gives definition of accounting. He defines accounting as *“system of recording and summarizing business and financial transactions in books and analyzing, verifying and reporting the results.”* Similarly investors use mental accounting to control where they spend their money on. It could be also defined as the ways used to code, categorize and evaluate financial decisions. According to mental accounting, investors evaluate financial decisions in separate mental accounts. In each account utilities, costs and outcomes of financial decisions take place. As an outcome is recorded into a mental account, approaching the decision from another perspective is getting harder. By this way, decision of investor may be affected in the wrong way.

Grinblatt and Han (2004) explain that decision-makers are inclined to put different types of gambles into separate accounts and apply prospect theory to each account. During this process, they ignore possible interactions between accounts.

Mental accounting could be categorized into three components: (Thaler, 1999a:184)

- How outcomes are perceived and experienced; how financial decisions are made and evaluated
- How activities are assigned to specific accounts
- In what frequency accounts are evaluated

A rational decision-maker treats various sums of money differently depending on where these sums are mentally categorized. Treatment will change based on how that sum is obtained (work, inheritance, gambling) and where it is intended to be used. (Leisure, necessities)

Combination of mental accounting with other biases (representativeness, overconfidence) leads investors to perceive risk inaccurately and may cause them to diversify inadequately. At the end, investors are exposed to high risks, low returns and even losses.

Mental accounting may cause investors to evaluate their investments on separate accounts. This could cause investors to disregard positions that offset or correlate across accounts. As a conclusion, suboptimal aggregate portfolio performance is attained.

2.7. OTHER BEHAVIORAL EFFECTS

2.7.1. Certainty Effect

Allais (1953) is the best known author, who counters to expected utility theory. He shows that people systematically violate expected utility theory. This is proved by the example which is given by Allais and used by Kahneman and Tversky (1979). At that example, individuals are asked to choose between a lottery which offers 3000 with 25 % probability and a lottery which offers 4000 with 20% probability. 65 % of individuals chooses the latter alternative. At the same study, when individuals are expected to make a choice between winning 3000 with 100%

probability and winning 4000 with 80% probability, 80 % of participants choose the first one. That tendency of individuals to choose the alternative that is certain is defined as certainty effect. Yet, expected utility theory foresees that people will be indifferent between two alternatives, since both provide equal utility.

According to Kahneman and Tversky (1979), certainty effect drives individuals to be risk averse in the choices which incorporates gains; and to be risk lover in the choices which incorporates certain losses. Cases in which individuals perceive a result that is only probable, as certain is named as pseudocertainty effect.

Certainty effect clearly constitutes a contradiction to expected utility theory. (Kahneman and Tversky, 1979: 265) According to certainty effect, individuals overweight certain events compared to outcomes which are only probable.

Kahneman and Tversky (1984) have explained certainty effect with an example. In the first problem of example, participants (N=81) are asked to involve in a two stage game in which participant will end the game without winning anything with 75 % probability and move into second stage with 25 % probability. If it moves into second stage it is asked to select a) a sure win of $30 (74 % of respondents select) b) 80% chance to win $ 45 (26% of respondents select). They state that choice must be made before game starts. At the second problem, they are asked to make a choice between a) 25% chance to win $ 30 (42 % of respondents select) b) 20 % chance to win $45 (58 % of respondents select).

In the first stage of the example, prospect a serves 25% probability to win $30 and prospect b offers 0.25*0.80=0.20 probability of winning $ 45. Namely two stages look identical in terms of probabilities and outcomes now. However preferences are not identical. At the first stage, majority prefers higher chance to win small amount; whereas at the second stage majority prefers lower chance to win higher amount. At the first problem, people reject the first stage. As a result of it, they face with opportunity to get guaranteed $ 30 and opportunity to get $ 45 with 80 % probability. As it could be seen from the example, the case in which a probable event is weighted as if it is certain is called pseudocertainty effect by Kahneman and

Tversky. This example proves violation of invariance. Violation of invariance is attributed to two factors by Kahneman and Tversky in the study they conducted in 1984: framing of probabilities and nonlinearity of decision weights.

2.7.2. Isolation Effect

Individuals tend to disregard components that are common for both alternatives and focus on components which are different to simplify making choice process. This tendency is called isolation effect. Levy (1992) states that isolation effect may lead to different preferences since there are several ways to decompose prospects as shared and disshared. This tendency leads to inconsistent preferences when same choice is presented in different forms. (Kahneman and Tversky, 1979:263)

Example of Kahneman and Tversky (1984) also constitutes an example to isolation effect since participants reject the first stage of the game and evaluate the game as if it includes only one stage. Yet, values of alternatives are same in both stages.

Values of the first stage: 80% probability $45
100% probability $ 30
Values of the second stage: 20% probability $45
25 % probability $30

2.7.3. Framing Effect

Framing is the notion how a concept is presented to individual matters. (Ritter, 2003:4) Framing effect could also be evaluated as a heuristic error. (Döm, 2003:22)

Prospect theory reveals that choice of individuals change depending on the presentation of the problem. Shafir et al (1997) state that when problem is presented in terms of final assets, people are inclined to prefer the risky alternative that has higher expected value. However, when same problem is presented in terms of gains and losses people tend to prefer status quo rather than risky prospect. Authors find this case in accordance with loss aversion principle. This is due because a potential $ 10000 loss offsets an equal chance of a $15000 gain.

Kahneman and Tversky (1984) asked participants of survey they conducted to make a choice between alternative programs which are designed to combat with a disease that is expected to kill 600 people. Consequences of alternative programs were presented one group in respect of number of people who will be saved (survival frame) and presented to other group in respect of number of people who will die (mortality frame) .

Specifically if program A is adopted, 200 people would be saved (400 would die), and if program B is adopted , 600 people would be saved with a one-third chance (none would die) and none would be saved with two-thirds probability (600 would die). At the end of survey it is found that a strong majority of respondents (72%) favored program A in the survival frame, whereas (78%) favored program B in the mortality frame.

Framing of problems affects behavior of individuals. Most familiar effects of framing on choices are loss aversion and diminishing sensitivity. Since pleasure of gains is less effective compared to disturbance of losses, framing that emphasizes on choice regarding losses will make that choice less attractive. Similarly, framing that shows losses relatively small will make choice more attractive.

Framing effect could be more easily seen in individuals who adopt narrow framing. Kahneman and Riepe (1998) consider that most decision makers adopt narrow framing and consider their decision problems one time and only guided by options available in making decisions. Authors also state that decisions made based on narrow frames inclined to show near-proportionality of risk taking, this means little risk tolerance in small gambles and too much risk taking in large gambles.

After all behavioral concepts are explained, it is reasonable to question why real world finance is still directed based on traditional theories. Thaler (2000) asks same question in a different way and he answers in a few sentences. He concludes that behavioral models are harder than traditional models. He also says that generation of models including fully rational and unemotional agents is easier than generation of models of quasi-rational emotional humans.

Until now efficient market theory and behavioral finance concepts, are tried to be explained with a general outlook. In the next section, our outlook will get narrower and our focus will be on the concept of "overconfidence" that is the main topic of this thesis. Despite a brief outlook to overconfidence is included in this chapter, in the next chapter it will be examined in detail in an organized way.

CHAPTER THREE

OVERCONFIDENCE HYPOTHESIS AND EMPIRICAL ANALYSIS

3.1. OVERCONFIDENCE HYPOTHESIS

Development of efficient market hypothesis and anomalies are given with literature in chapter 1. In the second chapter behavioral finance, which comes into being because of the insufficiency of the traditional theories in explaining the way things are in financial world, is examined. The aim of this chapter is to determine whether "overconfidence hypothesis" is valid for ISE or not. Before econometric analysis, literature of overconfidence will be presented. After then, model framework will be explained and finally analysis will be made.

Interdisciplinary character of economics has been increasing with the use of improvements from other disciplines like sociology, psychology and even neurology in recent years. By this way, economic behavior of individual agents and market can be better explained.

Skala (2008) asserts that psychological findings are started to be included in economic models starting from 1970s, but most rapid development of the trend begins with 1990s. After then some puzzles of financial market, which could not be solved by standard economic theory, are accounted once overconfident investors are assumed. Even De Bondt and Thaler (1995) evaluate overconfidence as the key factor that is needed to understand trading puzzle. They also note that "Perhaps the most robust finding in the psychology of judgment is that people are overconfident." Ko et al (2007) state that overconfidence could exist in many aspects of human behavior and because of that reason it is perceived as an important factor in financial markets. It is believed to explain excess trading, long-term reversals and excess volatility.

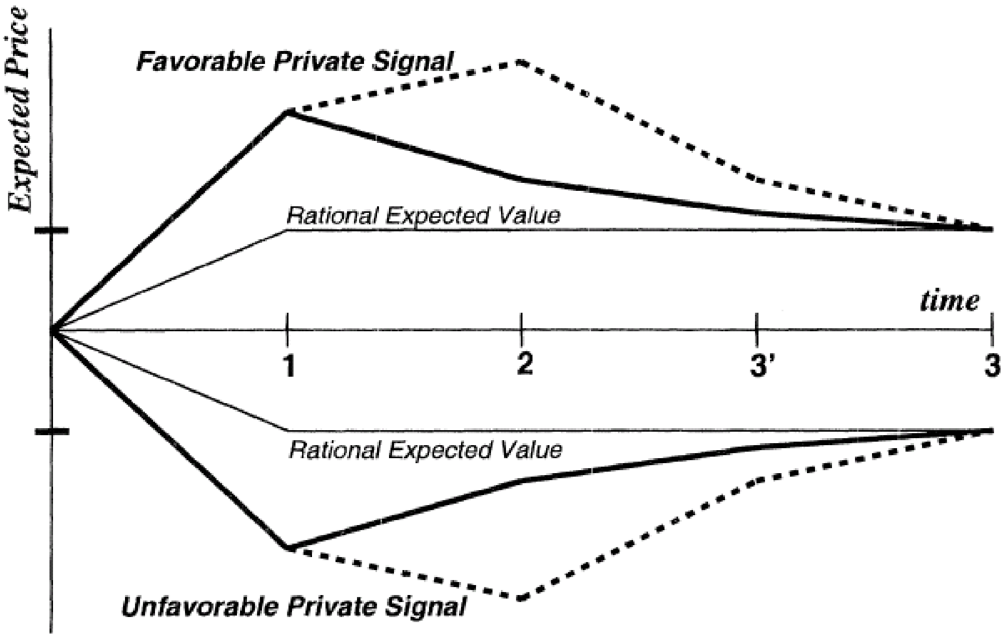
Despite it takes its roots from psychology, overconfidence has been influential in other disciplines like finance. There are various studies showing impacts of overconfidence on different disciplines. Camerer and Lovallo (1999) identify overconfidence as a possible explanation for persistent high rates of entrepreneurial entry, in spite of the frequency of entrepreneurial failure. From another perspective, Malmendier and Tate (2005) use overconfidence to explain high rates of corporate merger and acquisitions. Study that is related to financial markets is done by Odean (1998). He states that high trading volume of the stock market could be explained by overconfidence. Plous (1995) specifies importance of overconfidence by saying: “No problem in judgment and decision making is more prevalent and more potentially catastrophic than overconfidence.” (Plous, 1993, p. 217)

Although many articles are written about the relationship between price changes and trading volume, a few articles are written about the relationship between returns and trading volume, and overconfidence. Statman et al (2006) point out scarcity of empirical work that is written on the subject of overconfidence. They attribute that result to lack of well-defined and testable implications.

Daniel, Hirshleifer and Subrahmanyam (1998) define overconfident investor as the one who overestimates the precision of his private information signal, but not of information signals which are received by publicly. According to Barber and Odean (2000), overestimation of private information makes overconfident investors to trade too actively and causes them to earn below-average returns in turn. Overconfident investors also tend to overestimate their beliefs, estimations and abilities. According to Skala (2008), overconfident investors not only overestimate precision of their information (to be more specific: overestimation of private signals and underestimation of public signals); but also they underestimate variance of signals or volatility of asset values.

Daniel et al (1998) show overconfidence on a graph in their research whose central theme is; overreaction of stock prices to private information signals and underreaction of stock prices to public signals.

Figure 5. Path of Overconfidence



(Daniel et al, 1998: pp.1847)

That graph indicates the path average price follows after a positive (upper curve) or negative signal (lower curve). Here, thin horizontal line represents fully rational price level. Upper curve represents the expected prices conditional on a private signal.

At this graph, private signal leads stock price on date 1 to overreact to new information. However at date 2 when noisy public information signals arrive, inefficient deviation of prices is partially corrected on average. Same thing occurs at date 3, when subsequent public information arrives. Authors call the phase prior to peak, *overreaction phase* and later phase *correction phase*. At the overreaction phase cov (P_2-P_1, P_1-P_0), is expected to be negative. On contrary, cov (P_3-P_2, P_2-P_1), is expected to be positive.

Overconfidence, which is a prevalent psychological bias, creates mis-pricing in the form of excess volatility and return predictability. Furthermore, it generates inefficiency in markets if no rational arbitrageurs exist to bring prices back to their fundamental values. However, Ko et al (2007) indicate that incentive of overconfident investors to acquire information is a countervailing effect which makes prices more informative and efficient even in the absence of rational traders. Authors (2007) assert that overconfidence makes markets more efficient; since overconfident investors believe that extra returns could be earned. With this belief they tend to invest in resources to acquire information related to financial assets. Authors investigate which of two effects is larger, incentive to acquire information or mispricing generated by overconfidence. They find that effect of information acquisition on price quality, dominates the mis-pricing caused by overconfidence. As a result, they assert that overconfidence generally improves market efficiency if its level is not extremely high.

It is a common characteristic of human to learn about his abilities by observing consequences of his actions. That learning process is exposed to attribution bias in most times. (Gervais and Odean, 2001:1) People exaggerate the degree to which they are responsible for their successes. This leads to overconfidence. Successful investor attributes his success into his own ability and updates his beliefs about its ability upward too much. Gervais and Odean (2001) develop a dynamic overconfidence model that changes with investor's success and failure. They conclude that overconfidence level is greatest for people who have a short trading history. Also they comment that with acquired experiences, people learn to make better self-assessments. Another inference is made by Chen et al (2007) stating that investors, who attribute past success to their own skills and past failure to bad luck, are more likely to be overconfident.

Overconfident investors overestimate the probability that their personal assessments are more accurate than others and they strongly believe in their own valuations. This tendency of overconfident investors intensifies differences of opinion. Grossman and Stiglitz (1980) who use rational expectation framework, assert that investors will trade as long as marginal benefit of trade equals or exceeds marginal cost of trade. Additionally, they assert that rational investors purchase information only when doing so increase their expected utility. However Odean (1998), Odean and Gervais (1998), and Caballe and Sakovics (1998) develop overconfidence models which predict that investors could trade even to their detriment. (Barber and Odean, 2000:774) Besides, overconfident investors trade too much and by this way reduce their expected utility. Overconfident investors also spend too much on investment information. They are also assumed to hold riskier portfolios, compared to rational investors who are risk averse in same degree.

Selection bias might cause market participants to become overconfident. Because generally in financial markets people, who believe that they have more ability to trade, take place either as dealers or brokers. And because of that reason, we may expect financial markets to be populated by those overestimating their ability.

Survivorship bias could also lead to overconfidence, since unsuccessful traders drop out of market or have to manage smaller wealth. If successful traders overestimate their contributions for their successes, they become more overconfident and tend to control more wealth. However, it is noteworthy to realize that it is not the overconfidence that makes them wealthy, but process of becoming wealthy makes them overconfident. Since they are wealthy, overconfident traders are less likely to be in danger of being driven out of marketplace. Gervais and Odean (2001) state that as investors get older, they will lose not only their wealth but also their confidence. They may even give up trading. However; authors also note that there will be always overconfident traders in markets where inexperienced traders enter and old traders die.

Miscalibration is only one manifestation of overconfidence. It is the difference between the accuracy rate and probability assigned regarding a given answer is correct. Skala (2008) defines overconfidence as a particular form of miscalibration, for which assigned probability that the answers given are correct exceeds the true accuracy of answers. Another manifestation of overconfidence is optimism. People tend to be too optimistic about future events. They expect positive events to happen to them more often compared to other people. Opposite is valid for negative events. Shortly their optimism could be explained by the phrase “The future will be great, especially for me.” (Taylor and Brown, 1988:197) This also causes them to become overconfident. Another manifestation of overconfidence is better than average effect. According to this effect, most people perceive themselves better than average and most see themselves better than others see them. Taylor and Brown (1988), also indicate that people have unrealistically positive views of themselves in their survey.

Essential concepts in overconfidence are already investigated by Fischhoff (1977). His findings indicate that people tend to be overconfident in answering questions that are moderate to difficult, whereas they tend to be under confident in answering easy questions. This is called “hard-easy effect”. That effect is also confirmed by Lichtenstein et al (1982).

Why financial market participants are expected to be overconfident? Odean (1998) answers that question, by saying people are usually overconfident. Most traders attempt to select stocks that will have higher returns than other assets. This is a difficult task and it is known that people are overconfident especially in implementing difficult tasks. In a way, here hard-easy effect shows itself. Similarly based on Barber and Odean (2001), overconfidence level increases as difficulty of tasks increase. Overconfidence level is greatest for forecasts with low predictability and for undertakings lacking fast clear feedback. Since selection of stocks which will outperform the market is a difficult task whose predictability is low and feedback is noisy, people are overconfident in selection of stocks. Griffin and Tversky (1992) comment that experts tend to show greater overconfidence compared to novices, since they have models and theories to overweight.

Overconfidence in one’s information is only one type of overconfidence. Traders might also be overconfident in the way they interpret information rather than information itself. Odean (1998a) examines how overconfidence affects the markets. He concludes that this depends on the person who is overconfident and how information is distributed.

3.1.1. Overconfidence and Trading Volume

Chen et al (2007) identify trading frequency as a common proxy for overconfidence. Most studies before and after Chen et al (2007) use it as proxy. Trading volume will also be used as a proxy in this thesis.

It is not logical to explain high trading volume of speculative markets, which is a frequent research topic in overconfidence hypothesis, on just rational grounds. Glaser and Weber (2004) identify factors that might induce trading as differences of information, existence of noise, liquidity trading and portfolio balancing. However based on Chuang and Lee (2006), trading motivated from hedging and liquidity purposes constitutes only a small portion of observed trading activity in the world. Chuang and Lee (2006) serve overconfidence as an advanced explanation for observed trading volume. Similarly, Barber and Odean (2000) count overconfidence as an explanation for high trading levels and poor performance of individual investors. Barber and Odean (2001), also identify overconfidence as the most simplest and powerful explanation for high trading volume of financial markets. They also conclude that investors who trade the most are hurt the most. Same authors (1999), use closing prices of stocks that are listed on NYSE, AMEX and NASDAQ for the date between 1987 and 1993 and find that although overconfident investors make more trades, they get lower returns.

In the model developed by Gervais and Odean (2001), as overconfident trader trades aggressively, expected trading volume increases. Volatility also increases as a result of successes trader has. Authors also assert that not only volume but also volatility increase with the degree of learning bias trader exposed. Nonetheless, authors also find it noteworthy to express, that above hypothesis does not say that excessive trading of overconfident investors is the unique source of excessive volatility.

Overconfidence increases trading volume since it makes investors to overestimate accuracy of their beliefs. They tend to regard their own beliefs in an exaggerated manner, whereas they tend to disregard other’s beliefs. Gervais and Odean (2001) point out that overconfidence is enhanced in investors who experience high returns even if same high returns are experienced by market as a whole. An old Wall Street adage (1998) warns traders to against this misconception: “Don’t confuse brains with a bull market.” Another Wall Street Adage is “Volume is relatively heavy in bull markets and light in bear markets.” This adage also shows that traders mostly attribute market gains they win in bull markets to their own ability and continue to trade further.

Based on Odean(1999), overconfident investors trade more. Odean (1998) , develops a model where overconfident investors trade more and have lower expected utilities compared to a fully rational investor. Rational investors assess their expected trading profits correctly, on contrary overconfident investors hold unrealistic beliefs about expected trading profits. As a result of it, rational investors will not make trades if expected trading profits do not offset transaction costs. However, overconfident investors make transactions even when their expected trading profits could not offset transaction costs. They do, since they overestimate expected trading profits.

Trading volume, which is thought to have effects on stock prices and price volatility, reflects the cumulative reactions of investors to new market information. Moreover, it is an indicator measuring the information flow to the market. (Kıran, 2010:1) Because of these reasons, it has a critical role in the process of formation of stock returns and volatilities. Trading volume also reflects the changes in the expectations of investors in the market. As a huge amount of information flows to market, number of overconfident investors increase and more trades take place.

Statman et al (2004) explain positive lead-lag relationship between returns and volume under a few headlines including disposition effect and overconfidence hypothesis. At the end of work they prepare, they record higher trading volumes after high returns. In consistence with overconfidence hypothesis, they find that stock trading volume (turnover) is positively related with lagged stock returns.

Statman et all (2006), differentiate investor overconfidence from disposition effect of Shefrin and Statman (1985). Authors qualify disposition effect as a desire of individual investors to sell stocks that have appreciated in order to realize gains, namely they perceive disposition effect as an attitude about individual stocks they currently hold. On contrary, they qualify investor overconfidence as a separate theory of trading activity that is related with investor beliefs about trading in general.

Deaves et al (2008) examine if overconfidence induces trading, by dividing overconfidence into three manifestations: calibration-based overconfidence, better than average effect and illusion of control. Calibration-based overconfidence can be defined as the overestimation of knowledge precision .Whereas, Better than Average Effect is defined as the tendency of individuals to see themselves smarter than average by Taylor and Brown (1988). Finally, illusion of control is the exaggerated belief of control on events. At the end of study, authors find calibration-based overconfidence and better than average effect as predictors of trading activity. Nonetheless, they could not record any impact of gender on trading activity.

Overconfidence is expected to increase not only trading volume and but also market depth. On contrary, it is expected to decrease expected utility. Moreover, its effect on volatility depends on the person who is overconfident. Overconfidence might also lead to higher market efficiency when effect of information acquisition on price quality, dominates the mispricing created by overconfidence. A consensus could not be reached about effect of overconfidence on trading profits. (Skala, 2008:43) Overconfidence hypothesis suggests that overconfident traders could make markets to under react to both information of rational traders and abstract, statistical and highly relevant information. Other type of information rational traders under react due to overconfidence is new information. Nonetheless, markets over react to salient, anecdotal and less relevant information. (Odean, 1998: 1887)

In Turkey, first study in the area of overconfidence is conducted by Korkmaz and Çevik (2007). Authors use closing prices and trading volume of 114 stocks between the date May 1995 and October 2006. They investigate the relationship between overconfidence and trading volume, overconfidence and volatility and overconfidence and risk perception. Based on causality test conducted, overconfident investors are found to have more tendencies to make more trades after positive returns they obtain. Moreover, it is investigated if excessive trades that are led by overconfidence cause index volatility. It is concluded that overconfidence causes volatility. For the overconfidence and risk perception relationship, which is examined by constituting three portfolios, no evidence could be found showing that overconfident investors invest in risky portfolios more intensely.

It is noteworthy to mention that overconfidence is a characteristic of people, not of markets. (Odean, 1998a:1888) Although some measures of market like trading volume are affected by overconfidence of different market participants in the same way, some measures like market efficiency are not. Because of that reason, Odean (1998a) examines overconfidence hypothesis by dividing traders into three segments: price takers in markets where information is disseminated broadly, strategic-trading insiders and market makers.

3.1.1.1. Overconfidence of Price Takers

In this model, signal is received by all traders and it is assumed that there are not noise traders.

- When traders are price takers, expected volume increases with the increase in their overconfidence.
- When traders are price takers, volatility increases with the increase in their overconfidence.
- When traders are price takers, overconfidence worsens quality of prices.
- When price takers are overconfident, their expected utility is lower. This is due; since it causes non optimal risk sharing. Overconfidence causes them to hold undiversified portfolios.
- When new information is overvalued (undervalued) by price-takers, price changes show negative (positive) serial correlation. This means sign of serial correlation of returns and price changes are same.

3.1.1.2. Overconfidence of a Strategic Insider

In this model, it is assumed that signal is only received by a single insider and noise traders are assumed to exist now.

- When traders are insiders, expected volume increases with the increase in its overconfidence.
- As overconfidence of insider increases, market depth increases.
- As overconfidence of insider increases, volatility of prices increases too.
- Price quality improves as insider overconfidence increases.
- Expected profits of insider decrease with increases in his overconfidence.

3.1.1.3. Overconfidence of Market-makers

- Overconfident market-makers set a flatter supply curve, which encourages more trading when traders are price sensitive.

- Overconfidence of a market maker may lower volatility, since overconfidence make them to perceive less risk in holding inventory and set flatter supply curve. Flattening supply curve reduces volatility.

As insider is overconfident, he makes more trading. Market maker answers it by increasing market depth. Overconfident market makers perceive their estimate of security's true value more precise. They believe that they are facing less risk by holding inventory. Therefore they flatten their supply curves, which also increase market depth.

Chuang and Lee (2006) conclude implications of overconfidence under four headlines. Firstly, overconfident investors tend to over react private information, whereas they under react to public information. Secondly as investors' overconfidence increases with market gains, investors tend to trade aggressively in next periods. Thirdly, excessive trading overconfident investors make contributes to observed excessive volatility. Lastly, as investors become overconfident, they begin to underestimate risk and invest in riskier assets more.

There are many studies which uses gender as a proxy. One of these studies is prepared by Barber and Odean (2001), showing that single men take on more risk compared to married men. Based on that study, one who takes on risk most to least could be counted like this: Single men-Married men- Married women-Single women.

Similarly, Barber and Odean (2001) record higher overconfidence among men compared to women. In consistence with overconfidence hypothesis they find that men trade more than women. In the study they conducted in 1999, authors also find that men trade 45 percent more actively than women when they use gender as a proxy. As last, Barber and Odean (2001) suggests that difference in confidence of men and women, is greatest for tasks which are in masculine domain. They also add that men are more competent than women in financial matters.

3.1.2. Overconfidence and Risk

According to expected utility theory, rational investors attempt to minimize risk and simultaneously maximize returns. On the other hand, prospect theory suggests that perceived risk is the risk that directs the behavior of people. Overconfident investors misevaluate the risk level. Those overconfident people believe that stocks they select will get higher returns and have low risk. Furthermore, Nofsinger (2001) asserts that overconfident investors have higher risk because of two reasons:

- Overconfident investors are inclined to buy high risk stocks which are generally stocks of small-size firms or new firms.

- Overconfident investors tend to make under-diversification.

Another explanation for higher trading volume, could be desire of overconfident investor to use his perceived superior ability to get high returns. Because of that reason, they underestimate risks of active stock investing and trade more often. (Chen et al, 2007:426)

3.1.3. Overconfidence and Internet

Frequent usage of Internet affects not only methods of people use to make shopping, take information but also it affects investment behaviors of them.

Internet has provided many advantages to investors like lower commissions, easiness in making transactions, easy access, and increased information flow. Nonetheless, these advantages may increase psychological biases of investors. By trading directly not through a broker, they may feel an exaggerated sense of control. Furthermore, huge amount of online investment data like past stock prices and past returns may confirm their beliefs and may cause them to become overconfident. (Barber and Odean, 2001:42) Additionally, internet has a role in increasing emotional factors like pride, regret, house money effect and geteventitis. (Döm, 2003:68)

There are studies which are written about the effects of internet on taxes, price competition and foreign trade in the literature. Most of them focus on the advantages of internet usage in making transactions. Some advantages Internet provides to investors are lower commissions, easier access to market, and reductions in market interruptions. However, Internet has not only advantages; but also disadvantages. It leads investors to make excessive and speculative transactions by increasing investors' confidence. Investigators find that investors, who make online transactions but initially make transactions by telephone, are more active and more likely to involve in speculative and less profitable transactions with the effect of overconfidence. (Sevim and Temizel, 2009:139)

Making investment is a hard process which requires investor to collect information, analyze it and make decision. Internet simplifies information processing and causes investor to get overconfident by making it possible for investors to make various analysis and comparisons easily. Such analysis and comparisons cause investors to misevaluate information and overestimate their ability to analyze information. This makes them to trust unnecessarily their own estimations. Overconfidence also causes wrong investment decisions, excess trading, and taking on too much risk and as a result of all portfolio losses. (Nofsinger, 2001: 23)

Fisher and Statman (2000) mention that there are two factors which are effective in reducing overconfidence;

- Quick feedback is essential regarding accuracy of judgments. For instance, people who make weather forecasts or place bet on horse-racing takes daily feedback. For this reason these people are better in estimating probability assignments. With increased feedback, overconfidence could be reduced.

- People should be encouraged to consider not only supporters of their beliefs; but also opponents of their beliefs. By this way, they could make inference regarding why their judgments could be wrong.

3.2. MODEL FRAMEWORK

3.2.1. Modelling of Time Series

First thing to do in modeling time series, is determining if time series is stationary or not. If it is not, it should be made stationary by implementing various processes. Due to fact that firstly unit root tests will be explained. After then ARMA (Auto-Regressive Moving Average) Model, which predicts value of target variable as a linear function of lag values (auto-regressive part) plus an effect from recent random shock values (moving average part), will be mentioned. Finally, EGARCH model and Granger Causality Test, which will be used to detect causality relation, will be mentioned. After models are explained, analysis will be made.

3.2.1.1. Unit Root Tests

By stationary series constant mean, constant variance and constant autocovariances for each given lag is referred. (Brooks, 2008: 318)

$$\text{Mean}=E(Yt)=\mu \qquad (1)$$

$$\text{Variance}=\text{Var}(Yt-\mu)^2 = \delta^2 \qquad (2)$$

$$\text{Covariance}=\chi k = E((Yt-\mu)(Yt\text{-}k-\mu) \qquad (3)$$

Since analysis that is made by using non-stationary time series give biased results of t-test, f-test and R^2 value; test of unit root is a required process. If time series are non-stationary, they will include trend. In this case, use of non-stationary data may lead to spurious regressions. Namely, variables that are not related in reality could seem to be related with.

Existence of unit root will be investigated by Dickey –Fuller test. First announcement of that test, is made by articles of Dickey D.A. and W.A Fuller that are published in Journal of American Statistical Association in 1979.

3.2.1.2. ARMA Process

By notation ARMA (*p*, *q*), model with *p* autoregressive terms (number of lagged dependent variables that model will have) and *q* moving average terms is referred. By AR (1) Model, it is tried to be mention that time series behavior of Y_t is largely determined by its own value in preceding period. This means what will happen in time t, is dependent on what happened in time (t-1). (Asteriou and Hall, 2007:232) Similarly implication behind MA (1) Model is that; Y_t depends on the value of immediate past error, which is known at time t. (Asteriou and Hall, 2007:236) General forms of the models are:

- For AR(p):

$$Y_t = \sum_{1}^{p} i\ \phi_i Y_{t-i} + \mu_t \quad \textbf{(4)}$$

- For MA(q)

$$Y_t = \mu_t + \sum_{1}^{q} j\ \theta_j\ \mu_{t-j} \quad \textbf{(5)}$$

And ARMA process will be a combination of those from autoregressive part (AR) and moving average part (MA). Model of ARMA (p,q) will be:

$$Y_t = \sum_{1}^{p} i\ \phi_i Y_{t-i} + \mu_t + \sum_{1}^{q} j\ \theta_j\ \mu_{t-j} \quad \textbf{(6)}$$

3.2.1.3. ARCH Models

On contrary to traditional econometric models that operate under assumption of constant variance; ARCH (Autoregressive Conditional Heteroskedasticity) model ,which is introduced by Engle (1982), allows the conditional variance to change overtime as a function of past errors while leaving the unconditional variance constant. (Bollerslev, 1986:307)

Bollerslev (1986) has developed GARCH Model, which allows a much more flexible lag structure. According to Bollersev (1986), extension of ARCH process into GARCH process bears much resemblance to extension of AR process to the general ARMA process.

In the ARCH (q) process the conditional variance is determined as a linear function of past sample variances only, whereas the GARCH (p, q) process takes into account not only past sample variances but also lagged conditional variances.

ARCH and GARCH specifications are symmetric. Since residual term is squared; they only matter the absolute value of innovation, but not the its sign. They assume that a big positive shock will have exactly the same effect in volatility of series as a big negative shock of the same magnitude. Nonetheless it has been observed that negative shocks (bad news:excess returns lower than expected) have a larger impact than positive shocks (good news: excess returns higher than expected) of the same magnitude for equities. (Asteriou and Hall, 2007:267) Nelson (1991) has realized that gap in the literature and has developed a model which accommodates the asymmetric relation between stock returns and volatility changes: EGARCH Model. EGARCH Model is a variance model; that matters not only magnitude of past errors, but also sign of them. It is mentioned as logarithmic.

$$\text{Log}\,(\sigma t^2) = w + \beta\,(\sigma^2{}_{t-1}) + \gamma\,\frac{\mu_{t-1}}{\sqrt{\sigma^2{}_{t-1}}} + \alpha\,\frac{|\mu_{t-1}|}{\sqrt{\sigma^2{}_{t-1}}} - \frac{\sqrt{2}}{\sqrt{\Pi}}$$

Advantages of EGARCH over pure GARCH models are:

- Since conditional variance is modeled in logarithmic level, $\sigma\, t^2$ is positive even when parameters are negative.

- If there is a negative relationship between volatility and return, with the help of γ that is negative, asymmetric movements could be modeled.

3.2.1.4. Granger Causality Test

The most frequent method, that is used to detect causality relationship between time series, is Granger Causality Method. Granger Causality Test bases on the view that current value of dependent variable is determined by lagged values of itself and independent variable. In order to determine accurate relationships by Granger Causality Test, data series are required to be stationary or required to be converted into stationary by taking first difference. Otherwise Granger Test implemented will give spurious causality relationships.

Granger (1969) has specified that, all definitions he makes assume that only stationary series are involved. If non-stationary series are included, existence of causality could change overtime.

In Granger Test , that uses trading volume and stock returns as variables, rejection of null hypothesis asserting that stock returns do not granger cause trading volume (β_{12j} =0, for all j) will provide validity of overconfidence hypothesis. (Chuang and Lee, 2006:2496)

3.2.2. Analysis of Overconfidence Hypothesis in ISE

Overconfidence hypothesis foresees a positive causality relation from stock returns to trading volume; additionally it foresees an increase in volatility which stems from excessive trading volume of overconfident investors. In this section, these relations will be tried to examine by implementing methodology of Chuang and Lee (2006). In the analysis of relationship between trading volume and stock return, Granger Causality Method will be benefited. In the analysis of volatility, ARCH-LM test will be implemented to residuals that are obtained by ARMA process. After then E-GARCH model will be benefited. Data set used includes monthly closing values of ISE-100 index and monthly trading volumes of ISE100 index, between the dates of April1991- Jan2011. Data is obtained from FOREKS.

Return series is attained through taking logarithmic difference of ISE100 index. Formula that is used to get return series is "$r_{Ise100} = \ln_{Ise100,t} - \ln_{Ise100,t-1}$"

Descriptive statistics that belongs to returns series is given below.

Table 2.Descriptive Statistics

	VOLUME (Lot)	RETURN
Mean	4030000000	0.031581
Median	1390000000	0.029859
Maximum	21200000000	0.586585
Minimum	180897.0	-0.494856
Std. Dev.	5.00E+09	0.142591
Skewness	1.224231	0.239058
Kurtosis	3.782300	4.862267
Jarque-Bera	65.24372	36.50425
Probability	0.000000	0.000000
Sum	955000000000	7.484657
Sum Sq. Dev.	5.90E+21	4.798373
Observations	237	237

The skewness for a normal distribution is zero, and any symmetric data should have a skewness near zero. Negative values of skewness indicate that data is skewed left; whereas positive values of skewness indicate that data is skewed right. Since we have positive skewness value, our data is skewed to right. By skewed right it is meant that the right tail is long relative to the left tail. Positive skewness also indicates that, it is more common to have large positive returns than large negative returns. (Bhattarai and Joshi, 2009: 458)

Kurtosis of the normal distribution is 3. (Brooks, 2008: 163) Positive kurtosis indicates a "peaked" distribution and negative kurtosis indicates a "flat" distribution. Since both our data of trading volume and data of return have kurtosis which are bigger than 3, our data have leptokurtic distribution. Leptokurtic distribution has fatter tails and more peaked at the mean compared to a normal distribution. Our finding is in consistence with the phrase of Brooks (2008) which states that a leptokurtic distribution is more likely to characterize financial time series.

When we examine Bera-Jarque stat, we test the null hypothesis of no deviations from normality. We reject the null hypothesis asserting normality at 5% significance level and find Jarque Bera statistic as significant. As a conclusion, we could say that neither return nor trading volume has normal distribution.

Firstly, we make seasonal adjustment by using weighted average method to trading volume. Moving average is a smoothing mechanism that is used to smooth out seasonal variation in the data. (Benzion et al, 2001:8) It is favorable to make seasonal adjustment; since elimination of seasonal movements increase accurateness of coefficient estimates in making econometric analysis by using time series. (Alper and Aruoba: 2)

Figures below indicate the graph of logarithmic return series whose first difference is taken and graph of seasonally adjusted trading volume series.

Figure 6. Graph of Seasonally Adjusted Trading Volume

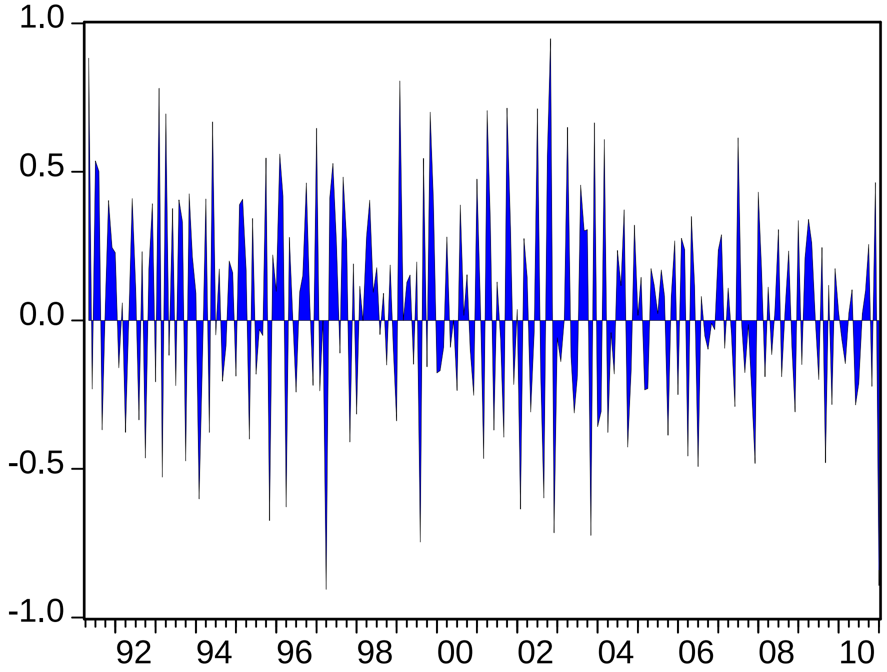
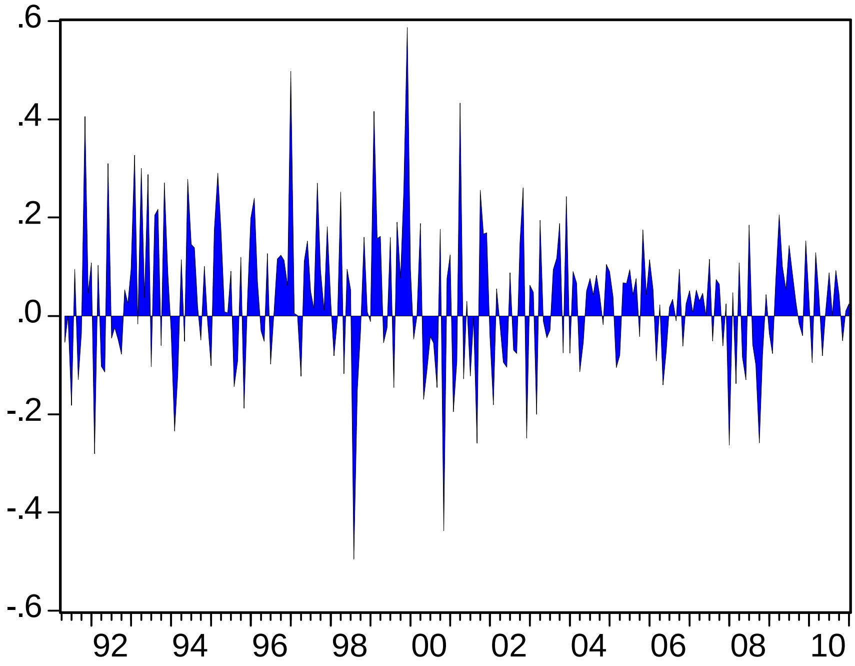


Figure 7. Graph of Logarithmic Return



From both figures, volatility clusters could be seen clearly. Mandelbrot (1963) asserts that large movements in the prices of financial assets are followed by large price movements, and slight price movements are followed by slight movements. In other words, he calls for the phenomena of volatility clustering. This case highlights the most important characteristic of financial variables, being dynamic not static.

Mandelbrot's finding is also valid for our data set. Large movements in logarithmic returns and trading volume are followed by large movements; similarly slight movements are followed by slight movements. This is an indicator of changing variance and volatility clustering.

After then, unit root tests will be implemented to determine if both time series are stationary. As mentioned before, use of non-stationary variables in analysis cause relations to seem as existing that do not exist in reality. Brooks (2008) states same thing by the sentence he uses "If standard regression techniques are applied to non-stationary data, the end result could be a regression that looks good under standard measures, but which is really valueless." (Brookk, 2008:319)

Many time series has trend and a relationship exists between its consequent values. A time series with a trend is not stationary and its usage in making estimations will cause to obtain wrong results. In order to prevent those results, series are required to be made stationary. (Armutlulu, 2000:316)

3.2.2.1. Unit Root Tests

Unit root tests will be investigated by Augmented Dickey-Fuller Test by taking the various cases into account. Here null hypothesis, which asserts that there is unit root and series is non-stationary, is tested.

3.2.2.1.1. For Trading Volume

Table 3. Unit Root Test of Trading Volume

	Mac-Kinnon Critical Values	
Significance Level	**no trend**	**trend**
1%	-3.458845	-3.998815
5%	-2.873974	-3.429657
10%	-2.573472	-3.138345
Probability values	0.8055	0.1676

ADF-stat is -0.839626 without trend and -2.890375 with trend. Since ADF-stat is smaller than critical values in absolute value, series of trading volume is said to be non-stationary. It is required to be made stationary.

When first difference is taken;

Table 4.Unit Root Test of Trading Volume when first difference is taken

	Mac-Kinnon Critical Values	
Significance Level	**no trend**	**trend**
1%	-3.459762	-3.999930
5%	-2.874376	-3.430196
10%	-2.573687	-3.138663
Probability values	0.0000	0.0000

ADF-stat is –5.736701 without trend and -5.796669 with trend. ADF-stat is bigger than critical values now. By this way, trading volume is converted into stationary.

3.2.2.1.2. For Return

Table 5.Unit Root Test of Return

	Mac-Kinnon Critical Values	
Significance Level	**no trend**	**trend**
1%	-3.457984	-3.997418
5%	-2.873596	-3.428981
10%	-2.573270	-3.137946
Probability values	0.0000	0.0000

ADF-stat is -15.60105 without trend and -15.73801 with trend. Since ADF-stat is bigger than critical values in absolute value, series of trading volume is said to be stationary.

Null hypothesis asserting existence of unit root has been rejected for return in all significance levels. This means that return series is stationary. However, null hypothesis has not been rejected for trading volume. Namely, it is non-stationary. It is converted into stationary form by taking first difference. Now, both series are stationary for all significance levels. At that point, series are available for further analysis.

3.2.2.2. Overconfidence and Trading Volume

If an investor is overconfident, he misattributes positive earnings he gets from stocks he holds to his superior ability and information. With this misevaluation, he increases the amount of trades in the subsequent period. Parallel to this view, Chuang and Lee (2006) assert that overconfidence hypothesis predicts causality from stock returns to trading volume. They establish hypothesis as below which we will also use:

"**H1:** Market gains (losses) increase (decrease) investors' overconfidence, and consequently they trade more (less) aggressively in subsequent periods."

First of all it is noteworthy to point out scarcity of empirical studies in the subject of overconfidence in the literature of behavioral finance. Statman et al (2006) attribute that scarcity to lack of well-defined and testable implications. The relationship between overconfidence and trading volume is investigated by Odean(1998), Barber and Odean (2000), Gervais and Odean(2001), Glaser and Weber (2004), Statman, Thorley and Vorkink (2006), Chuang and Lee (2006), Korkmaz and Çevik (2007) for different time periods.

Granger Causality Test will be employed to test if a relationship exists between stock returns and trading volume. Formally, with reference to Granger (1969) if the prediction of Y using past values of X is more accurate than the prediction without using X in the mean square error sense, where Ωt is the information set at time t, then X Granger-causes Y.

We will use autoregressions below to test the causality between trading volume and stock returns.

$$V_t = \alpha_{11} + \sum_{1}^{p} j\, \beta_{11} V_{t-j} + \sum_{1}^{p} j\, \beta_{12j} R_{t-j} + \varepsilon_{1t} \qquad \textbf{equation1}$$

$$R_t = \alpha_{21} + \sum_{1}^{p} j\, \beta_{21} V_{t-j} + \sum_{1}^{p} j\, \beta_{22j} R_{t-j} + \varepsilon_{2t} \qquad \textbf{equation2}$$

Here, V symbolizes seasonally adjusted trading volume, whereas R symbolizes return of ISE100 index.

In equation 1; if β_{12j} is statistically significant, a better forecast of future volume could be obtained by including both past values of return and past values of volume. So, we conclude that returns cause volume. If a standard F-test does not reject the hypothesis that $\beta_{12j} = 0$ for all j, then returns do not cause volume. In Granger Causality Test with two variables, rejection of null hypothesis asserting that “Return does not Granger Cause Lnlot” validates the overconfidence hypothesis. (Korkmaz and Çevik,2007:142) In our analysis β_{12j} is statistically significant and a causality relationship is found from return to volume. This inference validates the overconfidence hypothesis.

In equation 2; if a causality relation exists from volume to returns, then β_{21} will be different from zero. If not only $\beta_{12j;}$ but also β_{21} are different from zero, (statistically significant) then a feedback relation exists between returns and trading volume. Since β_{21} is not statistically significant in our regression, no feedback relation exists.

As a first step, Granger Causality test involves estimation of a VAR Model. We constitute a VAR model and determine lag number based on Akaike information criteria. We use three lags based on Akaike information criteria.

Table 6. Results of Granger Causality Test

Lag=3	F-stat	Prob
Return does not granger cause Lnlot	2.65706	0.04918
Lnlot does not granger cause return	1.51350	1.21179

Based on the result of Granger Causality Test (at 5% significance level), we could not reject the hypothesis assuming a causality relation from Lnlot to return. However, we reject the null hypothesis which asserts that "Return does not granger cause Lnlot". By this way, it could be said that in the short term there is a unidirectional relationship from return to trading volume. In other words, returns have predictive ability for movements in trading volume. This case serves finding which is in consistence with overconfidence hypothesis.

As last, we could prove existence of a positive relationship between return and trading volume by the help of a correlation matrix.

Table 7. Correlation Matrix

	LNLOT	**RETURN**
LNLOT	1.000000	0.536820
RETURN	0.536820	1.000000

3.2.2.3. Overconfidence and Volatility

Psychologists call self-attribution phenomena in many studies. As they imply, it refers the tendency of individuals to attribute their successes to their ability and attribute their failures to chance or other external factors. It is clear in the phrase of

Langer and Roth (1975) “Heads I win, tails it’s chance.” When public information is in agreement with his information, investor’s overconfidence grows excessively. However it does not fall commensurately when public information contradicts with his private information. (Daniel et al, 1998:1845) This could be thought as an indicator of overconfidence. From previous studies, it could be inferred that self attribution leads overconfidence to increase.

Studies about stock market volatility state that variance changes overtime and best model explaining such conditional variance variation is ARCH Models. ARCH Models, which have wide usage area in finance and macro economy, are developed to model volatility in time series. Arch model is firstly used by Engle (1982) in order to model variance of inflation and after then it is used for modeling return volatility of various financial assets. (Okay, 1998: 36)

It is necessary for trading volume to be auto correlated and stationary, in order to be used in autoregressive conditional heteroskedasticity models (ARCH) as explanatory variable. Autocorrelation of trading volume causes heteroskedasticity in returns and if series are not stationary, effect of trading volume on volatility will be misleading. (Kıran, 2010:101) Furthermore if parameter of the trading volume significant and positive, this addresses to positive effect of trading volume on volatility.

Before starting to analysis, we examine stationarity and autocorrelation of variables. At the end of unit root tests, we have observed that trading volume has unit root, whereas return has no unit root. When we took first difference of trading volume, we have met the requirement of being stationary. Based on Durbin Watson statistic that is attained from OLS procedure, trading volume is found as autocorrelated. By this way, we meet the requirements, to use trading volume as an explanatory variable, in the ARCH model.

Return volatility could be obtained by using ARCH Model. Also, there is a growing interest in GARCH Models that parameterize time-varying conditional variances of stochastic processes. Following Nelson (1991), EGARCH Model is used to measure return volatility which has advantages over ARCH and GARCH models.

In the first place, by using EGARCH model we eliminate the restrictions of ARCH and GARCH models that require positive constraints on the estimated coefficients. From another perspective, on the GARCH model conditional variance depends on not sign of the disturbance term but magnitude of disturbance term. GARCH also fails to capture the negative asymmetry that is observed in many financial time series. EGARCH model relieves this problem by modeling the standardized residual as a moving average regressor in the variance equation while preserving the estimation of the magnitude effect. (Chen et al, 2001:167)

Kim and Kon (1994) find EGARCH model as the most appropriate model for stock indices, whereas they find GJR-GARCH model as the most descriptive model for individual stocks. Since we use ISE-100 index as data, we prefer E-Garch model. Nelson (1991) shows e-GARCH Model under these statements:

- $R_t = \mu_t + \eta_t$
- $\eta_t \mid (\eta_{t-1}, \eta_{t-2}, \ldots) \sim GED(0, h_t)$
- $\ln h_t = \omega + f_1 \dfrac{|\eta_{t-1}| + k\,\eta_{t-1}}{\sqrt{h_{t-1}}}$

In this modeling, R is the stock return, μ is the mean of R_t conditional on past information, and h_t is the conditional volatility. Volatility parameter k shows the asymmetric effect in the EGARCH model.

Odean(1998) , Gervais and Odean (2001) indicate that as overconfidence increase, volatility of a risky asset increases. Namely our second hypothesis could be established as shown below;

“**H2:** Excessive trading of overconfident investors in securities contributes to observed excessive volatility.”

An empirical framework, which allows us to identify if observed excess volatility stems from excessive trading due to overconfident investors, will be used.

Procedure we implement which uses aggregate stock market data to examine how excessive trading of overconfident investors affects volatility is firstly studied by Chuang and Lee (2006) .Trading volume will be decomposed into two components by following Chuang and Lee (2006) and Korkmaz and Çevik (2007) .

$V_t = \alpha + \sum B_j R_{t-j} + \varepsilon_t$ (Chuang and Lee, 2006:14)

$V_t = \sum B_j R_{t-j} + [\ \alpha + \varepsilon_t\ ]$

In that model, constant and residual terms are thought to define component of the trading volume that is unrelated to overconfidence (NONOVERt). Whereas, the difference between trading volume and the constant and residual terms is thought to define component of trading volume that is related to overconfidence due to past stock returns (OVERt) .

After then, we put these two components of trading volume into conditional variance equation of Garch specifications.

- $R_t = \mu_t + \eta_t$
- $\eta_t |\ (\eta_{t-1}, \eta_{t-2}, \ldots) \sim GED(0, h_t)$
- $\ln h_t = \omega + f_1 \dfrac{|\ \eta_{t-1}| + k\ \eta_{t-1}}{\sqrt{h_{t-1}}}$
- $\ln h_t = \omega + f_1 \dfrac{|\ \eta_{t-1}| + k\ \eta_{t-1}}{\sqrt{h_{t-1}}} + f_2 \ln h_{t-1} + f_3 OVER_t$
  $+ f_4\ NONOVER_t$

In this modeling, R is the stock return, μ is the mean of R_t conditional on past information, and h_t is the conditional volatility. Volatility parameter f_1 (C4) shows the asymmetry (leverage) effect in the EGARCH model, whereas f_2 parameter refers to weight of previous period's conditional volatility on the conditional volatility of time t. Additionally, f_3 shows overconfidence effect on volatility, whereas f_4 shows other factors of volatility**.** To observe if overconfidence volume increases conditional volatility, we compare f_3 with f_4**.** If $f_3 > f_4 > 0$, overconfidence volume is said to increase conditional volatility. Statistically significance of estimated f_3 , coupled with the observation that $f_3 > f_4$ proves that overconfidence component of trading volume is positively correlated with market volatility, that means high volatility could be partially justified based on investor overconfidence**.** Also**,** if estimated f_4 parameter is statistically significant, it could be suggested that overconfidence is not the unique cause of high market volatility. (Chuang and Lee, 2006: 23) By this way, we distinguish excessive trading made by overconfident investors, from other factors affecting market volatility

In order to implement GARCH models, it is required for series to have ARCH effect. To determine if ARCH Effect exists, firstly we implement ARCH-LM test to residuals that are obtained by ARMA (3,3). ARMA (3,3) is found as the most appropriate one due to lowest AIC criteria it provides. We test the null hypothesis of homoscedasticity in ARCH-LM Test for various lags. We reject the null hypothesis at %5 significance level which means that ARCH effect exists for only lag 24. ARCH-LM test stats are given below;

Table 8. Results of ARCH-LM Test

	F-stat	**Prob (F-stat)**	**Obs*R-squared**	**Probability**
Lag=1	0.051453	0.820754	0.051887	0.819811
Lag=2	0.720521	0.487598	1.450791	0.484133
Lag=5	1.171830	0.323904	5.862757	0.319803
Lag=10	1.290411	0.237322	12.79535	0.235340
Lag=15	1.509779	0.104008	21.97960	0.108340
Lag=24	1.894488	0.009945*	41.42976	0.014936

Since ARCH effect exists, EGARCH Model could be used now. Parallel to this, f3 parameter for OVER part and f4 parameter for NONOVER part is generated. In generation process of f4, constant and residual term is taken into account. For f3, as explained above difference between trading volume and constant and residual term is considered. Result of the regression could be seen at Table 8.

Table 9. Results of E-GARCH Model

LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1)) + C(6)*F3 + C(7)*F4

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.013031	0.008146	1.599641	0.1097
Variance Equation				
C(2)	-0.285250	0.125539	-2.272208	0.0231
C(3)	-0.065786	0.056076	-1.173161	0.2407
C(4)	-0.024447	0.071753	-0.340710	0.7333
C(5)	0.932455	0.022605	41.25075	0.0000
C(6)	1.169921	0.333499	3.508016	0.0005
C(7)	88.98278	48.69553	1.827330	0.0677
T-DIST. DOF	26.82737	58.02746	0.462322	0.6439

R-squared	-0.017619	Mean dependent var	0.031944
Adjusted R-squared	-0.048862	S.D. dependent var	0.142784
S.E. of regression	0.146231	Akaike info criterion	-1.244764
Sum squared resid	4.875422	Schwarz criterion	-1.127346
Log likelihood	154.8822	Durbin-Watson stat	2.003504

The EGARCH Model does not confirm the existence of leverage effect; because the measure of leverage effect, γ (C4), is not significant. In other words, stock market gives reaction to good news and bad news in the same way. If γ was statistically significant, we would conclude that positive shocks (good news) generate less volatility than negative shocks (bad news). (Kıran, 2010:3)

f2 (C5) coefficient, which shows the long-term effects on volatility, is found significant and considerably high in this model. (It is 0.932455) This means that it takes long time for effects of shocks to vanish.

At the end of regression, ***f3*** and ***f4*** parameters are found statistically significant at % 10 significance level. However since ***f3*** is not bigger than ***f4,*** overconfidence component of trading volume is not said to be increasing conditional volatility for the period used in econometric analysis. This case is not in consistence with overconfidence hypothesis. Based on that result, high market volatility does not stem from overconfidence of investor.

Research findings show a positive relation between trading volume and return which is in consistence with overconfidence hypothesis. However, in the framework of volatility, findings that are not in consistence with overconfidence hypothesis are obtained. Existence of leverage effect also can not be proven by E-GARCH model.

CONCLUSION

Fama describes an efficient market as the one in which prices always fully reflect available information. Based on efficient market hypothesis investors can not be able to get abnormal returns, since new information is reflected in prices immediately and accurately. However, investigations about market efficiency show that it could be possible to get abnormal returns by benefiting from anomalies.

Neither only traditional financial theory which asserts that individuals are rational, nor only psychological theories could individually explain investment decisions of investors. At that point behavioral finance, which asserts that individuals are quasi-rational, comes into being. Behavioral finance attempts to incorporate insights from psychology to economics. It fills the gap included in traditional finance by taking into account mental biases.

Behavioral finance phenomenon has been a popular research area for a long time. Although there is a vast of study regarding behavioral finance concept generally, overconfidence phenomenon is a relatively undiscovered area in behavioral finance. Particularly, in Turkey only a few studies are written about overconfidence concept. This is a result of lack of testable implication in empirical area.

This thesis aims to contribute the literature by examining overconfidence in ISE-100 index. Previous studies conducted in Turkey, which use similar methodologies, are different from the content of this thesis, since one of them uses ISE-30 index and other attempts to examine overconfidence in individual stocks of ISE.

In the beginning of thesis, efficient market hypothesis is discussed by its assumptions, criticisms and literature. After then behavioral finance concept is examined in detail. At the last section not only detailed discussion of overconfidence, but also empirical tests are involved. Empirical part uses monthly closing values and trading volumes of ISE-100 index for the period of April1991- Jan2011. ADF Test is implemented to specify if data is stationary. After then modeling is made.

Relationship between overconfidence and trading volume is investigated via Granger Causality Test. After its existence is proved, sign of causality is determined by correlation matrix and a positive relation is found. Relationship between overconfidence and volatility is examined via E-GARCH Model and it is found that high market volatility does not stem from overconfidence of investors. This study could be extended by implementing same procedure on industrial indexes if trading volumes on the base of indexes can be found.

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APPENDICES

APPENDIX A

Selection of Most Appropriate ARMA Model

	AIC	Log-Likelihood
ARMA(1,1)	-1.036940	125.3589
ARMA(1,2)	-1.029601	125.4929
ARMA(1,3)	-1.026916	126.1760
ARMA(2,1)	-1.026567	124.6217
ARMA(2,2)	-1.017300	124.5328
ARMA(2,3)	-1.014785	125.2372
ARMA(3,1)	-1.026026	125.0450
ARMA(3,2)	-1.017553	125.0537
ARMA(3,3)	-1.085594*	134.0145*

A minimal value for AIC indicates that you have chosen the number of groups that produces the best fit without overfitting. It is possible to assign each of the data points to one of the groups with a maximum likelihood approach. Because of that reason we select ARMA (3,3) as the most appropriate model and we continue with ARCH-LM Test and EGARCH Test.