WHAT FACTORS AFFECT BEHAVIORAL BIASES?:

EVIDENCE FROM INDIVIDUAL TURKISH STOCK INVESTORS

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BOĞAZİÇİ UNIVERSITY
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Thesis Abstract

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In this thesis, five behavioral biases of individual Turkish stock investors are analyzed: overconfidence, familiarity bias, representativeness heuristic, status quo bias and disposition effect. Using buy and sell transaction data for the year 2011, the commonality of and factors affecting these biases, as well as how these biases relate to each other and investor return performance are analyzed. Behavioral biases are common among individual stock investors. Male investors, younger investors, investors with a lower portfolio value, and investors in low-income and low-education (less developed) regions exhibit more overconfidence and familiarity bias. Female investors, older investors and investors with high portfolio values are more subject to representativeness heuristic and disposition effect. Individuals in the opposite edge of overconfidence scale are subject to status quo bias. Overconfidence and representativeness heuristic deteriorate wealth while status quo bias and disposition result in higher trade performance. Familiarity bias has a non-monotonic effect on return; lower (higher) level of familiarity bias has a negative (positive) effect on return. Results of this thesis extend the findings of the behavioral finance literature to emerging markets based on a unique nationwide dataset.

Tez Özeti

Bülent Tekçe, "Davranışsal Eğilimleri Belirleyen Faktörler Nelerdir?: Türkiye'de Yerleşik Bireysel Hisse Senedi Yatırımcılarından Bulgular"

Bu tezde, kendine fazla güvenme, aşina olana eğilim, benzer olana eğilim, statüko eğilimi ve elden çıkarma etkisi olmak üzere Türkiye'de yerleşik tüm gerçek kişi hisse senedi yatırımcılarının gösterdiği beş davranışsal eğilim analiz edilmiştir. 2011 yılına ait alım satım işlemleri kullanılarak, eğilimlerin yaygınlığı, eğilimleri etkileyen faktörler, eğilimlerin birbirleri ve yatırım performansları ile ilişkileri analiz edilmiştir. Davranışsal eğilimler bireysel hisse senedi yatırımcıları arasında yaygındır. Erkek, genç, daha düşük portföy büyüklüğü olan ve düşük gelir / düşük eğitim seviyesine sahip (daha az gelişmiş olan) bölgelerde yerleşik yatırımcılar kendine fazla güvenme ve aşina olana eğilimi daha fazla sergilemektedir. Kadın, yaşlı, daha yüksek portföy büyüklüğü olan yatırımcılar ise benzer olana eğilime ve elden çıkarma etkisine daha fazla meyillidir. Kendine fazla güvenme endeksinin düşük ucundaki bireyler statüko eğilimi göstermektedir. Kendine fazla güvenme ve benzer olana eğilim serveti olumsuz etkilemekte, statüko eğilimi ve elden çıkarma etkisi ise daha yüksek getiri sağlamaktadır. Aşina olana eğilimin getiriye etkisi monotonik değildir; daha düşük (daha yüksek) aşina olana eğilimin getiri üzerine etkisi negatifdir (pozitifdir). Bu tezin sonuçları, ülke çapında bir veri seti kullanılarak, davranışsal finans literatüründeki bulguları gelişmekte olan piyasalar için de doğrulamaktadır.

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CHAPTER 1

INTRODUCTION

The vast majority of models that try to explain financial markets assume that investors evaluate risky decisions according to Expected Utility Theory (EUT). EUT assumes that preferences can be represented by expectation of a utility function if they satisfy a set of axioms that guarantee rationality assumption of decision makers. Under these axioms, EUT explains how decision makers should behave under uncertainty.

However, empirical evidence in both psychology and behavioral economics and the finance literature show that individuals do not behave rationally and violate the axioms of Expected Utility Theory. The models based on the rationality assumption are not sufficient enough to explain the puzzles observed in the financial markets. Kahneman and Tversky (1979) criticize the EUT and propose an alternative model, Prospect Theory. The authors state that biases which irrational individuals possess may stem from beliefs and preferences. A major departure of Prospect Theory from Expected Utility Theory is the rationality of the agents. Relaxing the rationality assumption for decision makers has very important implications in many fields analyzing decision-making under uncertainty such as economics and finance. If individuals are not rational, then it is highly probable that the investment decisions of individuals are also irrational.

Prospect Theory is used to explain many puzzles that rational models fail to explain. Equity premium puzzle, excess volatility, excessive trading, stock return predictability can be better explained by behavioral finance models based on Prospect

Theory. Barberis and Thaler (2003) provide a good summary of models that try to explain these puzzles using both Prospect Theory and beliefs.

Another important contribution of behavioral models is that they assume prices are not efficient as Efficient Market Hypothesis proposes. Efficient Market Hypothesis assumes that investors use all relevant information about an asset and discount expected cash flows to obtain the fundamental value of the asset in a rational manner. The prices may deviate from the fundamentals with the existence of irrational investors. The literature presented by Daniel et al. (2002) support the view that markets are not efficient and that investor biases affect security prices substantially.

However, there are also objections to behavioral models. As Subrahmanyam (2007) presents, theoretical behavioral models are ad hoc and explain only some stylized facts. Although it is true, behavioral models are based on how people actually behave rather than how they should behave. In this sense, behavioral models are descriptive rather than normative. Besides, these models are based on extensive experimental evidence. Hirshleifer (2001) also summarizes objections to behavioral models, yet give counter examples of a fully rational approach to asset pricing.

Investor irrationality may depend on many factors such as individual and cultural differences. Vissing-Jorgensen (2004), using an investor optimism survey data conducted by UBS and Gallup from 1998 to 2002, finds that irrational behavior such as representativeness heuristic, self-attribution bias, disposition effect, under-diversification and status quo bias are weaker for more sophisticated investors. Cultural differences such as degree of individualism or collectivism has a significant impact on cognitive styles, risk attitudes and behavioral tendencies of inhabitants. Individualism is a more

evident trait in Western countries, such as the USA and the UK, whereas Eastern countries like China and India tend to exhibit collectivism. Hofstede (2001) finds that Turkish people are more collectivist compared to the USA, the UK and Western Europe. Additionally, the ambiguity avoidance index, which captures the tolerance of a society for uncertainty and ambiguity, is high among Turkish citizens.

The majority of the behavioral finance literature analyzes individual investors in developed markets such as the USA, the UK and Western Europe. However, Turkey as an emerging market and the Istanbul Stock Exchange (ISE) in Turkey have important characteristics that would appear to be worth analyzing. The ISE is a member of the World Federation of Exchanges (WFE) and the Federation of European Securities Exchanges (FESE). As a leading / advanced emerging market stock exchange, the ISE is recognized as an investable market according to the US Securities and Exchange Commission (SEC) and Japan's Financial Services Agency. The ISE has one of the highest turnover ratios among world stock markets, which may be related to the biases among Turkish stock investors. According to World Bank, in 2011, the ISE ranks fifth in terms of turnover ratio after Italy, the Republic of Korea, China and the USA. Trading volume in the ISE is relatively high and provides a liquid market for investors. Although foreign investors hold around 65% of free float in the ISE, they constitute only around 15% of the trading volume. Foreign investors mostly prefer ISE30 and ISE100 (major benchmark) stocks, which have high market capitalization, high liquidity and are representative of the sectors they operate in. Trading volume and liquidity are provided mostly by local individual investors.

Using nationwide data, this thesis focuses on five behavioral biases of all individual Turkish stock investors that may affect the portfolio selection process of the investors: overconfidence, familiarity bias, representativeness heuristic, status quo bias and disposition effect in a collectivist country. Using all buy and sell transaction data for the year 2011, this thesis analyzes how prevalent these behavioral biases are among individual investors, which demographic factors – namely age, gender, wealth, experience and region of residence – affect these biases, and how these biases relate to each other and investor return performance.

Among these five biases, overconfidence and disposition effect are more widely studied. Shefrin and Statman (1985), Odean (1998b), Odean (1999), Barber and Odean (2000), Grinblatt and Keloharju (2001b), Barber and Odean (2001), Chen et al. (2007) and Grinblatt and Keloharju (2009) are only a few.

Overconfidence results in aggressive trading behavior and overconfident investors may have to pay a significant amount of commissions. Moreover, overconfident investors may hold riskier portfolios than they should tolerate due to their underestimation of risk. Overconfidence not only affects financial markets and prices, but also individuals as they may make suboptimal investments and deteriorate wealth. Hence, it is important to determine the level of and the factors affecting overconfidence.

Familiarity bias is important in the sense that it explains how investors decide to purchase a stock for reasons other than rational motives. Familiarity bias simply implies investing in "the familiar assets". Such an approach leads to passing up higher returns and/or lower risks available in the total asset universe that investors are not familiar with. Familiarity bias may also lead to lack of diversification.

The psychology literature shows how the representativeness heuristic can explain expectation formation, which affects investment decisions. There are several studies which focus on how investors extrapolate past price trends to predict future prices in order to measure representativeness heuristic. The representativeness heuristic may deteriorate wealth and also distort asset prices.

Status quo bias implies that individuals may refrain from making decisions and keep their current position (status quo) to prevent potential future regrets. This view can easily be extended to finance in the sense that individuals may prefer to keep their stock investment portfolios unchanged. Status quo bias may result in investors refraining from trading while overconfident investors trade excessively. This is because most investment decisions have a default alternative of doing nothing and investors may choose this default alternative if they are not in a position to evaluate the advantages and disadvantages of alternatives such as selling the stock.

There is a vast amount of literature measuring disposition effect among different type of investors (individual, professional) in different contexts (IPOs, common stock investments, small stocks) using different methods. The disposition effect leads investors to suffer from losses for unnecessarily long periods of time. Also, investors may not fully take advantage of gains as they tend to realize gains too soon. Both of these two effects result in investors suffering from losses and losing opportunity of further gains.

The results show that behavioral biases are common among individual Turkish investors. Overconfidence and familiarity bias are higher among male investors, young investors and investors with low portfolio values, and investors in less developed

regions. Findings for the status quo bias are consistent with overconfidence results, and individuals exhibiting status quo bias are in the opposite edge of overconfidence scale. Representativeness heuristics estimates show that individual Turkish stock investors do not seem to be positive return chasers. Demographic factors affect the representativeness heuristic in just the opposite way they do the overconfidence and familiarity bias. Although statistically significant, the representativeness heuristic is not economically different across different investor groups. The disposition effect is higher among female investors, older investors and investors with high portfolio values. Results for all biases are robust to the use of different proxies, various subsamples and regression models.

The trade performance of investors is also analyzed in order to understand whether biases impact return performance. Return calculations are based on matched sell transactions with one or more buy transactions within 2011. Results show that overconfidence is hazardous to wealth, as mean return decreases with increasing turnover. Investment decisions of overconfident investors seem not to be justified. As opposed to overconfidence, higher status quo bias leads to higher returns. Although they do not trade too much, investors exhibiting status quo bias seem to make better sell decisions compared to overconfident investors. At moderate levels of familiarity bias, investors have lower returns; however, mean return increases at high familiarity bias levels. This is probably due to the information effect, as the more investors are familiar with the stock, the better decisions they may make. Investors chasing stocks with positive past returns end up with lower returns. These investors are probably late in catching the momentum train and have poor timing in investment decisions. As the

definition of disposition effect implies, investors exhibiting disposition effect have higher returns.

The findings of this thesis contribute to the behavioral finance literature in a number of ways. First, a unique nationwide data set is used to analyze five different biases as well as the relationships among them unlike most of the studies in the literature, which are limited to a subset of investors and look at one bias at a time. This thesis focuses on an emerging market with high collectivist attitudes as opposed to the widely studied developed countries with individualistic attitudes, with the aim of reaching a better understanding of the behavioral biases of investors in such countries.

Chapter 2 presents the psychology and behavioral finance literature regarding behavioral models and five behavioral biases of concern in this thesis. Based on the findings of the literature, hypotheses are developed in this chapter.

In Chapter 3, the data and research methodology is developed. Details of measurement methods of each behavioral bias taking literature into account are also discussed in this chapter.

Chapter 4 presents the results. In this chapter, the commonality of each behavioral bias is discussed based on descriptive and statistical analysis. Demographic factors affecting behavioral biases are analyzed using regression analysis. The relationship between trade performance and behavioral biases are also analyzed. The final part of this chapter presents the relationship among biases.

The final chapter presents the implications of the study and suggests future research areas to be addressed.

CHAPTER 2

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

The first section of this chapter presents the literature review regarding the behavioral models. The subsequent sections present the literature review for overconfidence, familiarity bias, representativeness heuristic, status quo bias and disposition effect and introduces the hypotheses for each bias.

Behavioral Models

The vast majority of models in finance and economics assume that investors evaluate risky decisions according to Expected Utility Theory (EUT). EUT assumes that preferences can be represented by the expectation of a utility function if they satisfy a set of axioms that guarantee rationality assumption of decision makers.

Suppose a lottery with uncertain outcomes is characterized by its pay-offs {x} and probability distribution p(x). Let L define the game. Then,

$L(x) = L(x, p(x))$

The axioms of rationality can be summarized as follows:

Completeness: Let L(x) and L(y) be two lotteries. Then, $L(x) > L(y)$ or $L(x) < L(y)$. This means that a decision maker prefers either x or y.

Transitivity: For every lottery, if $L(x) > L(y)$ and $L(y) > L(z)$, then $L(x) > L(z)$. This means that if a decision maker prefers x over y and y over z then, the agent prefers x over z.

Independence: if $L(x) > L(y)$ then $L(ax+(1-a)z)) > L(ay+(1-a)z))$. This means that if x is preferred over y and both lotteries x and y are mixed with a third lottery z, then the preference does not change for the new mixed lotteries.

Continuity: if x is preferred over y and y over z, then there exists a p ($0 \leq p \leq 1$) such that $y \sim px+(1-p)z$. This means that p(x) is continuous.

Based on these axioms, EUT explains how decision makers should behave under uncertainty. EUT assumes that utility of a risky prospect is linear between probabilities between 0.99 and 1 and between 0.10 and 0.11. However, experimental evidence shows that due to the certainty effect, preferences are nonlinear. According to EUT, different framing of the same choice problem should give rise to same preferences (independence), whereas experimental evidence supports just the opposite. The preferences may change by framing the same problem in a different setting.

What is more, rational decision-making under uncertainty generally assumes risk aversion, whereas risk seeking is consistently observed in certain cases such as lotteries (low probability of winning a high prize) and sure losses (individuals prefer a high probability of large loss to with expected value higher than a sure loss). Losses loom larger than gains, which means suffering from a specific level of loss may be more than pleasure from same level of gain.

Empirical evidence in both psychology and behavioral economics and the finance literature show that individuals do not behave rationally, contrary to what Expected Utility Theory assumes. The models based on the rationality assumption are not sufficient to explain the puzzles observed in the financial markets. Several models have

been proposed to explain the experimental evidence that violates EUT. Behavioral finance models have emerged with the aim of explaining the violations of EUT and relaxing the basic assumption that agents are fully rational. Kahneman and Tversky (1979) criticize the EUT and propose an alternative model, called Prospect Theory. As Barberis and Thaler (2003) state, Prospect Theory may be the most promising theory to explain financial markets. The authors state that biases which irrational traders possess may stem from beliefs and preferences. Beliefs affect how agents form expectations, and preferences affect how investors evaluate risky decisions.

According to Kahneman and Tversky (1979),

- people underweight outcomes that are uncertain in comparison with outcomes that are obtained with certainty (certainty effect), which implies that individuals are risk-averse in choices involving sure gains and risk-seeking in choices involving sure losses'
- people may have inconsistent preferences when the same choice is presented in different forms (isolation effect).

Based on these observations, the authors developed Prospect Theory which assumes that

- value is assigned to gains and losses rather than final states of wealth
- decision weights are used to calculate values rather than probabilities
- value function is normally concave for gains and convex for losses (Fig. 1)
- decision weights are generally lower than corresponding probabilities, except in the range of low probabilities (Fig. 2)
- value function is steeper for losses than gains

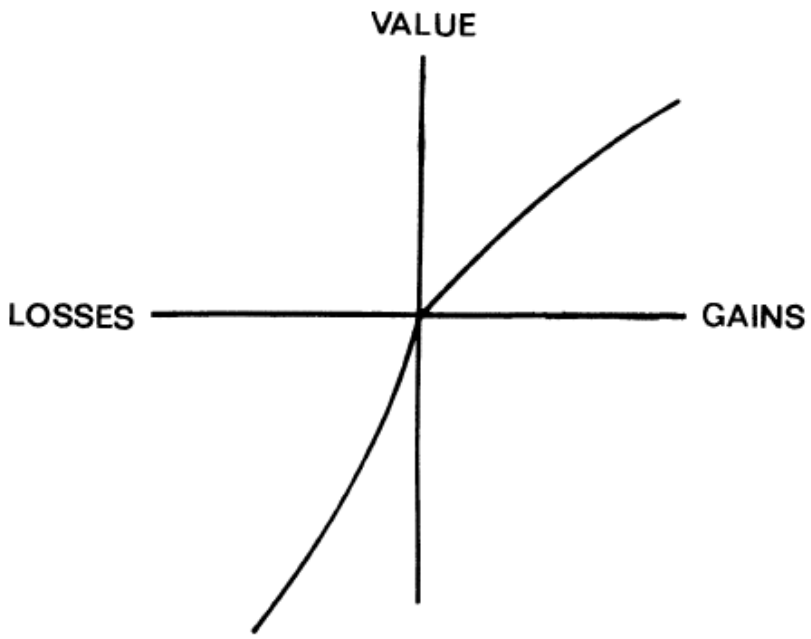

Fig. 1 Hypothetical value function

An essential part of the Prospect Theory is that value is defined over changes in wealth (gains and losses) rather than final states. Since gains and losses depend on reference point and reference point is subject to change, value is also based on reference point defining the current wealth state.

Another important feature of Prospect Theory is that decision weights used to compute value are lower than the stated probabilities which are used to compute expected utilities except in the range of low probabilities. A hypothetical weighting function can be seen in Fig. 2.

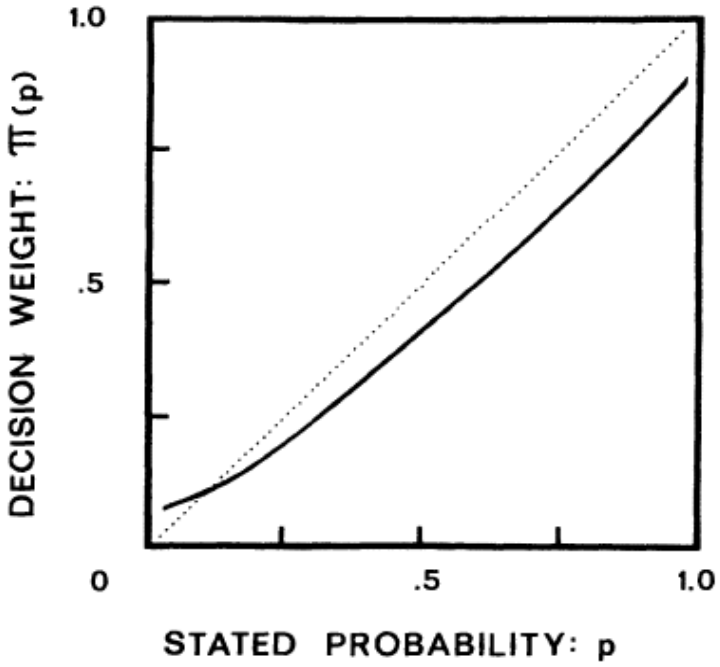

Fig. 2 Hypothetical weighting function

Tversky and Kahneman (1992) improved the Prospect Theory by employing cumulative rather than individual decision weights which can be applied to decision-making under uncertainty as well as risk. Diminishing sensitivity and loss aversion are introduced to explain curvature of value function and weighting functions and valuation is two-part cumulative (valuation is different for losses and gains). The authors call this new model Cumulative Prospect Theory.

In Cumulative Prospect Theory, the entire cumulative probability function is transformed to decision weights rather than individual probabilities separately, and cumulative decision weights are applied to gains and losses separately, which extends Prospect Theory to uncertain as well as risky prospects.

Diminishing sensitivity entails that the impact of a given change in probability diminishes with its distance from boundaries (certainty and impossibility). Cumulative weighting function is concave near 0 and convex near 1 both for gain and losses. The cumulative weighting function can be seen in Fig. 3.

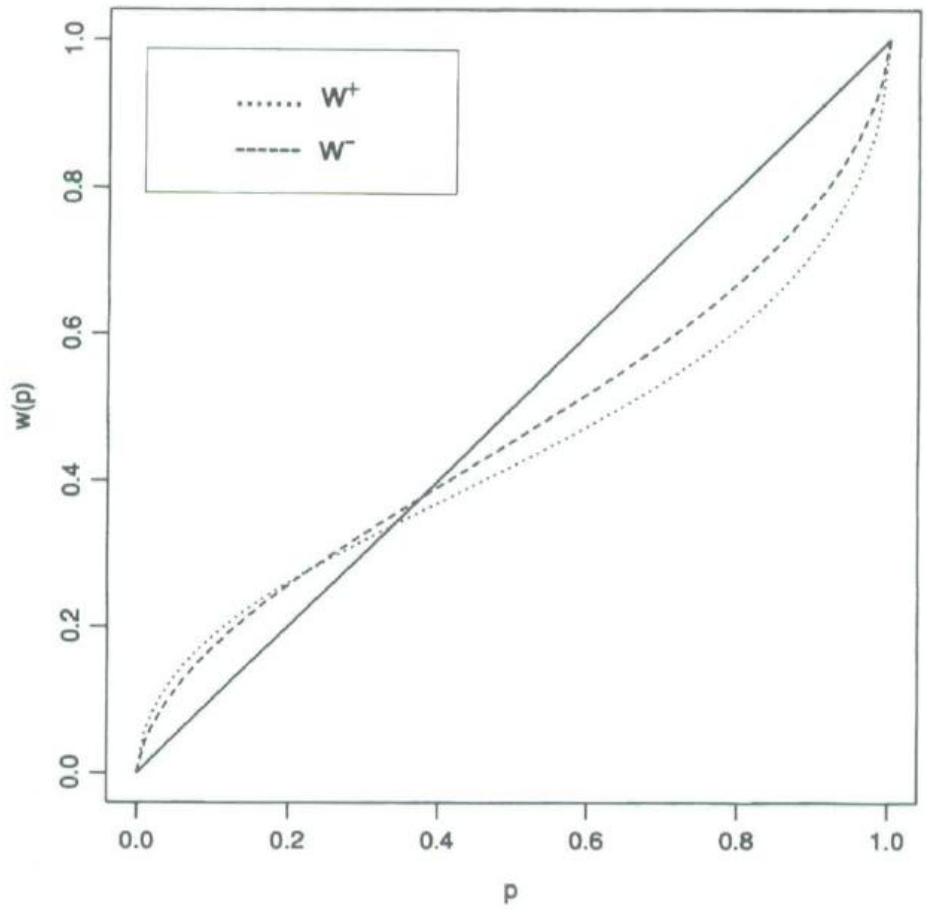

Fig. 3 Hypothetical cumulative weighting function

Fig. 3 shows that probabilities are overweighed in the small probability region (from 0 to 0.4), which contributes to popularity of lotteries and insurance. Probabilities are underweighted in the high probability region (from 0.4 to 1), which implies risk

aversion in choices between probable gains and sure things and risk seeking in choices between probable and sure losses. Pronounced asymmetry of value function (Fig. 1) for gains and losses implies loss aversion in the domain of losses.

A major departure of Prospect Theory from Expected Utility Theory is in the rationality of agents. Prospect Theory does not impose rationality as an assumption. Relaxing rationality assumption for decision makers have very important implications in many fields analyzing decision-making under uncertainty such as economics and finance. If individuals are not rational, then it is highly probable that investment decisions of individuals are also irrational.

Prospect Theory is promising in the sense that it can be used to explain many puzzles that rational models fail to explain. Equity premium puzzle, excess volatility, excessive trading, stock return predictability can be better explained by behavioral finance models based on Prospect Theory. Barberis and Thaler (2003) provide a good summary of models that try to explain these puzzles using both Prospect Theory and beliefs.

Another important contribution of behavioral models is that they assume that prices are not efficient as the Efficient Market Hypothesis proposes. Efficient Market Hypothesis assumes that investors use all relevant information about an asset and discount expected cash flows to obtain the fundamental value of the asset in a rational manner. The prices may deviate from the fundamentals with the existence of irrational investors. If any deviation from fundamental value is observed, rational investors will step in and bring back the price to fundamental value by exploiting arbitrage opportunities. However, eliminating arbitrage opportunities can be costly and so risky

that rational agents may not bring them back to fundamentals. The literature presented by Daniel et al. (2002) supports the view that markets are not efficient and that investor biases substantially affect security prices.

However, there are also several objections to Prospect Theory and behavioral models. As Subrahmanyam (2007) presents, theoretical behavioral models are ad hoc and explain only some stylized facts. Although it is true, behavioral models are based on how people actually behave rather than how they should behave. In this sense, behavioral models are descriptive rather than normative. Besides, these models are based on extensive experimental evidence. Hirshleifer (2001) summarizes objections to behavioral models and gives counter examples to a fully rational approach to asset pricing.

Objections to Psychological Approach	**Objections to Fully Rational Approach**
Alleged psychological biases are arbitrary.	Rationality requires impossible power of calculations.
Experiments that generate alleged psychological biases are not meaningful.	Evidence does not support a rationality assumption in asset pricing.
It is easy to generate a theory for psychological biases using ex post data.	It is easy to generate theories for rational models using ex post data.
Rational traders should arbitrage away mispricing.	Irrational traders should arbitrage away efficient prices.
Rational investors should make wiser decisions and get richer.	Irrational investors will bear more risk and get richer.

Nevertheless, Prospect Theory and behavioral models have been theoretically and empirically proven to be working. The rationality assumption implies that decision

makers have limitless cognitive capabilities to evaluate alternatives and choose the one which maximizes utility. However, Tversky and Kahneman (1974) show that people rely on a limited number of heuristic principles which reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations. As Kahneman (2003) states, most judgments and most choices are made intuitively. Since individuals have limited cognitive resources, they cannot process all available information, and the decision-making process is subject to heuristic simplification, which causes behavioral biases.

Heuristic simplifications and cognitive limitations result in behavioral biases which may lead to anomalies such as consistent mispricing of assets (long term deviation of prices from fundamental values), excess volatility in asset prices, suboptimal behavior of individual investors (excessive trading, under-diversification, reluctance to realize losses, and so on).

Barberis and Thaler (2003) provide a summary of models that try to explain some of these anomalies such as the equity premium puzzle, excess volatility, excessive trading, and stock return predictability using both the Prospect Theory of Kahneman and Tversky (1979) and beliefs. Daniel et al. (2002), Black (1986), De Long et al. (1990), Shleifer and Vishny (1997), Barberis et al. (2001), Hirshleifer (2001), Daniel et al. (2002), and Subrahmanyam (2007) show that investors are not rational or markets may not be efficient, and hence prices may significantly deviate from fundamental values due to the existence of irrational investors.

Psychology literature defines numerous behavioral biases that may affect decision-making. A subset of these biases is of interest to behavioral finance literature, as these

biases affect financial investment decisions. The effect of these biases on investment decisions not only impacts individuals but also the financial markets as a whole.

Overconfidence

Overconfidence is simply the unmerited confidence in one's own judgments and abilities. Odean (1998a) describes overconfidence as the belief that a trader's information is more precise than it actually is. This is equivalent to narrow confidence intervals in predictions. According to Chen et al. (2007), the literature of psychology and behavioral science characterizes people who behave as if they have more ability than they actually possess as being overconfident. Daniel et al. (1998) define an overconfident investor as one who overestimates the precision of his private information signal, but not of information signals publicly received by all. According to the authors, overconfidence is dynamic and time varying depending on the outcomes of the previous decisions.

Odean (1998a) presents a good summary of overconfidence in different professions such as clinical psychologists, physicians and nurses, investment bankers, engineers, entrepreneurs, lawyers, negotiators and managers. In the case of financial markets, he finds that overconfidence affects financial markets. He also maintains that overconfidence increases expected trading volume, increases market depth, and decreases the expected utility of overconfident traders.

Overconfidence may stem from different factors such as self-attribution bias, illusion of control, optimism about future events, confirmation bias, better than average effect and miscalibration.

Self-attribution is attributing successful outcomes to one's own skill but blaming unsuccessful outcomes on bad luck. Miller and Ross (1975) argue that successful outcomes result in greater self-attribution of performance than failing or neutral outcomes. The more individuals relate success with their abilities, the more overconfidence in skills and decision-making capabilities increase. Hence, it can be assumed that overconfidence tends to increase after decisions with successful outcomes. Kunda (1987) finds that people tend to generate and evaluate causal theories in a self-serving manner. The author argues that people tend to relate desirable outcomes to their own attributes, whereas they are reluctant to relate undesirable outcomes to their own skills. This finding also supports Miller and Ross (1975). Kunda (1987) thus suggests that people have optimistic beliefs that good things will happen to them and bad things will not. This is also related to optimism, which increases overconfidence.

The illusion of control is the tendency for people to overestimate their ability to control events that they have no influence over. After a series of experiments, Langer (1975) proposes that if factors from skills (choice, familiarity, involvement to process and so on) are introduced to pure chance situations, individuals feel inappropriately confident. This is related to the illusion of control. As the definition implies, the illusion of control is directly related to overconfidence. Langer defines the illusion of control as an expectancy of a personal success probability inappropriately higher than the objective probability would warrant. This expectancy may be due to individuals' motivation to control their environment. According to Langer, another possible reason is that skill and chance factors are so closely associated with individuals' experiences that they cannot discriminate between skill and chance factors. The findings imply that individual

investors may think that they can change the outcome of a pure chance process by introducing their skills. This implication can be extended to investment area. Outcomes of an investment decision may be affected by many factors that are beyond the control of the investor. However, individual investors, due to the illusion of control, may mistakenly feel and believe that they can control all factors and that their decision will turn out to be successful.

Unrealistic optimism is simply confidence about the future or the successful outcome of something. It is the tendency to take a favorable or hopeful view. Weinstein (1980) states that people are unrealistically optimistic about their future life events due to factors such as degree of desirability, personal past experiences, higher perceived probabilities, and perceived controllability. These different dimensions may lead to optimistic beliefs and expectations among individuals.

Confirmation bias is the tendency for people to favor information that confirms their arguments, expectations or beliefs. According to Russo and Shoemaker (1992), when making predictions, people often lean towards one perspective and the natural tendency is to seek support for the initial view rather than look for disconfirming evidence. Thus, individuals stick to confirming evidence and disregard disconfirming ones.

The better-than-average effect implies that people think they have superior abilities than the average individual. Hence, they tend to believe they are in the best class among peers. Svenson (1981) shows that people think they are more skillful and less risky drivers than an average driver when they compare themselves with others.

Such a better-than-average belief may lead to overconfidence in finance, as individuals may falsely believe that they can outperform others in their investment decisions.

Calibration refers to how individuals can assess the correctness of their estimates. A miscalibrated agent assumes a lower level of mistake than he/she actually makes. A well-calibrated agent can correctly assess the number of mistakes he/she makes. This implies that a miscalibrated agent underestimates the number of mistake he/she makes. Such an agent makes decisions based on this false belief, which may result in overconfidence.

Different forms of overconfidence reveal that overconfident investors believe that their decisions will prove to be correct and that they will expect higher returns than average. However, this is not necessarily the case, and overconfident investors may deteriorate wealth due to their investment decisions. Barber and Odean (2000, 2001, 2002) argue that overconfidence can explain poor trading performance related to high trading levels and conclude that that trading is hazardous to wealth. Hence, it is hypothesized that overconfidence diminishes the trading performance of individual Turkish stock investors.

Theoretical models developed by Kyle and Wang (1997) and Wang (2001) show that overconfident investors may survive and even make a profit. Hirshleifer and Luo (2001) developed a model in which overconfident and rational investors coexist. The main result of their model is that the long-run steady-state equilibrium always involves overconfident traders as an important part of the population. The findings of Fischoff et al. (1977), Russo and Shoemaker (1992), Griffin and Tversky (1992), Kahneman and Riepe (1998) support these theoretical models and show that overconfidence is common

among decision makers. Not only individuals, but financial market professionals as well may exhibit overconfidence. Deaves et al. (2010) use a monthly survey data gathered from 350 market practitioners who work in finance companies in Germany. The results reveal that individuals are overconfident (in the sense that they are miscalibrated). Overconfidence seems to increase after successful forecasts and decreases after failures, and overconfidence increases with experience. The authors also find that overconfidence increases after high market returns in recent past. In line with the findings, it is hypothesized that overconfidence is common among individual Turkish equity investors.

Barber and Odean (2001) test whether men are more overconfident than women. The authors use data from a nationwide brokerage house between 1991 and1996 by focusing on common stock investments of households. They find that men trade 45% more than women. The findings of Barber and Odean (1999), Chen et al. (2007), Acker and Duck (2008), Graham et al. (2009), Grinblatt and Keloharju (2009), and Hoffmann et al. (2010) also support the view that men are more overconfident than women. Therefore, it is hypothesized that Turkish male investors are more overconfident than female investors.

Chen et al. (2007) use transaction data of a large Chinese brokerage house to analyze overconfidence among Chinese investors. The authors find that individual investors in China trade more frequently than those in the US. Acker and Duck (2008) use a stock market game and predictions of examination marks to measure overconfidence among Asian and British students. They find that Asian students are more overconfident than British students. Fan and Xiao (2005) and Statman (2010) show that individuals in different societies and cultures may have different behavioral biases

which may affect their financial decisions. Hofstede (2001) shows that Turkish people are more collectivist, which is also a more evident characteristic in Eastern societies such as China, compared to the USA, the UK and Western Europe.[1] Hence, it is hypothesized that individual Turkish stock investors are more overconfident than individual investors in the US.

Graham et al. (2009) find that wealthy and highly educated investors are more likely to perceive themselves as competent, implying overconfidence. On the other hand, Ekholm and Pasternack (2007) confirm that investors with smaller portfolios are more overconfident compared to investors with larger portfolios, as these investors are more experienced and wealthy. Hence, it is hypothesized that sophisticated investors are less prone to overconfidence.

Familiarity Bias

According to Fox and Tversky (1995), when people are offered two alternatives, they prefer the one that they are familiar with. This is also valid for stock selection since people are better informed about the securities that they are familiar with compared to the ones that they are not. According to Huberman (2001), this is the defining property of familiarity. The author argues that preference for the familiar and distaste for and fear of the unfamiliar leads to the basic result that people simply prefer to invest in familiar securities. Merton (1987) develops a capital market equilibrium model in which each investor knows only a subset of available securities. The subset differs across investors. The model implies that investors make their investment decisions from the stocks that

[1] Based on data available on http://geert-hofstede.com/

they are familiar with. Using data from Sweden, Massa and Simonov (2006) find that familiarity affects individual investors' investment decisions.

Investors face a challenge when they decide to buy a security among many alternatives that is beyond the capabilities of human capacity to analyze and select. Hence, when deciding what securities to invest in, individual investors should simplify the search process. This means that individual investors focus on securities that grab their attention most. The literature demonstrates that familiarity, whether in the form of more marketing / advertising, media citation, being local to investor or analyst coverage, affects investment decisions.

Taking search costs into account, Sirri and Tufano (1998) hypothesize that investors purchase equity funds that are easier or less costly to identify. These may be among funds with higher marketing expenses, and those receiving greater media attention which increases brand awareness. Investors will probably put this fund in a "consideration set" from which they select products. The authors find that a larger share of media citation is related to faster growth in funds. Although the authors state that they cannot disentangle the direction of causality, the findings indicate that the more familiar the investors are with a security, the more likely they are to buy it, as it will be in the "consideration set" of the investor. Jain and Wu (2000) and Barber et al. (2005) also find that individuals invest in securities that they are familiar with, familiarity being increased through advertising.

Grinblatt and Keloharju (2001a) argue that home bias may be a part of a larger phenomenon in which investors exhibit a preference for the familiar companies. They point out that familiarity has many facets, such as the distance of the headquarters of the

firm from the investor or a similarity in culture and / or the language of the firm may be the roots for familiarity. Using these facets as proxies, the authors find that investors in Finland are more likely to buy stocks that are familiar to them. Coval and Moskowitz (1999) show that the preference for investing close to home also applies to domestic stock portfolios. The authors show that investment managers exhibit a strong preference for locally headquartered firms, particularly for small, highly levered firms. As the firm size increases, more non-local investors add the security to their portfolio. Coval and Moskowitz (2001) confirm these findings also for mutual fund managers. Zhu (2002) analyzes individual investor preference for nearby investments for equities and finds that both institutional and individual investors tend to hold stocks of companies with nearby headquarters (individuals exhibiting a higher degree of bias). In line with the findings, it is hypothesized that a significant portion of individual Turkish equity investors invest in stocks that they are familiar with.

Barber and Odean (2008) argue that professional investors are less prone to familiarity bias than individual investors. Hence, it is expected that sophisticated investors have a lesser degree of familiarity bias.

Representativeness Heuristic

People tend to classify objects and thoughts. When they confront a new phenomenon, based on their categorizations, they classify the new object or thought to the existing ones. This perceptual framework helps individuals process new information by simultaneously incorporating past experiences and help individuals give quick responses to unknown events. Representativeness heuristic describes the degree to which a sample is similar to another sample in all essential characteristics. Kahneman and Tversky

(1972) argue that people who follow the representativeness heuristic evaluate the probability of an uncertain event or a sample by the degree to which it is similar in essential properties to its parent population and reflects the salient features of the process by which it is generated. Tversky and Kahneman (1971) argue that people have erroneous intuitions about chance. Due to the law of small numbers, they view a sample randomly drawn from a population highly representative of the population, to be a good description of representativeness heuristic. Tversky and Kahneman (1974) state that people often predict the future value of a stock based on representativeness. If this is the case, investors will be inclined to buy stocks whose price has been increasing recently (extrapolation bias). Grether (1980) shows that individuals give too little weight to prior information and too much weight to evidence. Andreassen and Kraus (1990) find that investors extrapolate recent past stock price trends which result in more purchasing after two successive bull periods and more selling after two successive bear periods. These are in line with the arguments of Tversky and Kahneman (1974).

Lakonishok et al. (1994) show that in the long run (3-5 years), value stocks outperform growth stocks, and that this cannot be attributed to the riskiness of value stocks. The authors argue that investors think recent past performance of growth stocks will continue in the future as they extrapolate the return trend of these stocks and invest in growth stocks. When it turns out that return patterns are not realized, value stocks outperform growth stocks in the long run. According to the authors, investors make judgment errors and extrapolate past growth into the future. Empirical research in finance literature identified two patterns in stock returns: underreaction over shorter periods (1-12 months) and overreaction in longer periods (3-5 years). Barberis et al.

(1998) develop a theoretical model to explain these two phenomena. The underlying basics of the model depend on representativeness heuristic as well as conservatism. Extrapolation of past returns is the form of representativeness in the model. Individuals who exhibit representativeness heuristic extrapolate past performance into the future. Representativeness in the model assumes that the short-term trend in the price movements will be followed in the longer term.

Benartzi (2001) examines retirement saving plans of S&P 500 firms and finds that there is a positive correlation between past returns and subsequent allocations to company stocks, and that correlation gets stronger as the return accumulation period lengthens. The author confirms the extrapolation hypothesis using a survey conducted on the Internet among Morningstar subscribers. According to survey results, past returns of stocks are likely to persist, which is supportive evidence for the extrapolation hypothesis. In line with literature, it is hypothesized that representativeness heuristic is common among individual Turkish stock investors.

Grether (1980) confirms representativeness heuristic for inexperienced or financially unmotivated subjects: however, the evidence is less clear for other subjects. Chen et al. (2007) find that representativeness heuristic is only applicable to individual investors; institutional investors are unaffected by the recent past return performance. Hence, it is hypothesized that sophisticated investors are less prone to representativeness heuristic.

Status Quo Bias

Most real decisions have a default alternative of doing nothing. Samuelson and Zeckhauser (1988) define status quo as doing nothing or maintaining one's current or

previous decision. In an experimental setting, the authors show that individuals stick to the status quo. According to authors, individuals exhibit status quo bias more when there are many alternatives in the decision set. The authors argue that status quo bias may stem from rational decision-making as well as biases such as loss aversion, regret aversion and avoiding cognitive dissonance.

As Tversky and Shafir (1992) state, choice always produces conflict because individuals have difficulties in trading off costs against benefits or comparing risks against value, which makes it difficult to make important decisions. When each alternative has its own advantages and disadvantages or when each alternative has risks, then individuals face difficulties in making a decision. This may lead individuals to refrain from making decisions and to sticking to their current positions or at least to delaying the decision and exhibiting status quo bias. The authors argue that conflicts about the alternatives can increase not only the tendency to defer choice but also the tendency to choose the default option (status quo).

Samuelson and Zeckhauser (1988) argue that status quo bias may stem from rational decision-making as well as biases such as loss aversion, regret aversion and avoiding cognitive dissonance. Similarly, Kahneman and Tversky (1982) and Ritov and Baron (1995) argue that the status quo may stem from regret aversion. Kahneman et al. (1991) argue that one implication of loss aversion is that individuals have a strong tendency to remain at the status quo when the disadvantages of leaving it are more than the advantages. Thus people tend to stick to the status quo in decision-making situations under uncertainty. This study explains status quo bias in terms of loss aversion. Another possible explanation to status quo bias is omission bias. Ritov and Baron (1992) argue

that since changing status quo requires an action and keeping status quo requires omissions of choices, individuals may prefer to omit alternatives and stick to the status quo to prevent evaluating alternatives and making decisions. Since there are numerous alternatives in equity investments, individuals may just omit the alternatives to prevent facing the difficulties of making decisions. However, the authors do not explain why people exhibit omission bias. It may be directly or indirectly related to loss aversion, regret aversion or cognitive dissonance, as Samuelson and Zeckhauser (1988) suggest.

Since there are numerous alternatives in equity investments, individuals may exhibit status quo bias to prevent facing the difficulties of making decisions. Madrian and Shea (2001) argue that the preference of a default contribution rate and plan in the 401(k) plan of employees in a large US corporation is related to status quo bias. Agnew et al. (2003) use the transaction data of participants from the retirement plan of a large firm in the US. They find that investors infrequently re-balance their portfolios and tend to maintain their initial asset allocations, implying status quo bias. Although a strand of literature shows that individual investors are overconfident and trade excessively, studies with retirement plans reveal that investors may exhibit status quo bias in their investment decisions. Since equity investments have many alternatives to decide among (whether to buy, sell or hold, when to buy/sell or what to buy/sell), and risks and benefits may not be evaluated easily, equity investors may be inclined to stick to the status quo (do nothing) or just defer the decision. As the psychology literature suggests, it is expected that a portion of stock investors keep their portfolio positions unchanged.

The status quo is related to reluctance to trade, whereas overconfidence is related to excessive trading. Hence, as Hoffmann et al. (2010) argue, it is expected that

individuals on the opposite edge of the overconfidence scale are subject to status quo bias.

Madrian and Shea (2001) find that men prefer a default plan to a lesser degree than women, and the default contribution rate declines significantly with compensation. Therefore, it is hypothesized that women exhibit a higher degree of status quo bias than men.

It is also hypothesize that sophisticated individuals exhibit status quo bias to a lesser degree than less sophisticated investors.

Disposition Effect

Disposition effect is the tendency to sell winners too early and hold onto losers too long. Disposition effect can be most easily observed in equity trading. Besides this, there are several studies showing that the disposition effect is also common, for example, in stock option exercises (Heath et al.,1999) and housing markets (Genesove and Mayer, 2001).

Shefrin and Statman (1985) argue that disposition effect stems from loss aversion, mental accounting and regret aversion. One of the most important implications of Prospect Theory is that individuals are loss-averse, meaning that they try to avoid losses. Mental accounting explains why investors do not realize losses in a stock to exploit a tax advantage and buy another stock similar to the one sold. Individuals tend to segregate different gambles (in the case of individual stock investors, investing in stocks) in different mental accounts and ignore the possibility of interaction among accounts. Hence, investors have difficulty in realizing losses in an account and invest for another account although the overall effect will be the gain due to tax advantage. Investors try to avoid regret in their decisions. The authors define regret as an emotional feeling

associated with the ex post knowledge that a different past decision would have fared better than the chosen one. Hence, they tend to avoid closing a stock account at a loss not to feel regret in the future. The authors calculate a round trip duration which denotes the length of time that an investor holds a stock before selling it. They find that ratio of number of transactions where a gain is realized to all realizations is around 60%. The authors argue this pattern implies disposition effect among investors.

Odean (1998b) finds that investors demonstrate a strong tendency to realize winners rather than losers, except in December. Tax motives lead to an opposite result in December. Odean looks for different alternatives to explain this tendency and argues that the disposition effect is the main reason. The findings are robust at different reference points (highest purchase price, first purchase price, and most recent purchase price). Weber and Camerer (1998), Barber and Odean (1999), Shapira and Venezia (2001), Brown et al. (2006), Barber et al. (2007), Grinblatt and Keloharju (2001b), Chen et al. (2007), and Barber et al. (2009) also find that individuals display the disposition effect and / or that disposition effect is persistent over periods in different countries. In line with findings, it is hypothesized that individual Turkish equity investors exhibit disposition effect.

Shapira and Venezia (2001) show that both professional and individual investors exhibit disposition effect, although the effect is much more emphasized for individual investors. According to Brown et al. (2006), traders with larger investment amounts tend to be affected less by disposition effect. Dhar and Zhu (2006) find that wealthy investors, investors employed in professional occupations (used as a proxy for financial literacy) and investors trading more often exhibit less disposition effect. Therefore, it is

expected that investors who are financially sophisticated are less prone to disposition effect.

CHAPTER 3

DATA AND RESEARCH METHODOLOGY

The first section of this chapter provides the definition and the descriptive statistics of the data used in this thesis. The next section develops the methodology to measure each bias as well as analyze the relationship between demographic factors, trade performance and biases.

Data

Nationwide data was used to look at the investment activities of individual Turkish stock investors during 2011. The data was from the Central Registry Agency (CRA), which consists of all buy and sell transactions as well as monthly stock only and total portfolio positions (stocks, funds, private sector bonds and warrants). Investor information on the demographics, region of residence and account opening date were also used for the analysis. According to CRA monthly statistics as of January 2011, the total number of individual Turkish stock investors was approximately one million. However, a significant portion of these investors were either dormant or had very low stock portfolio value. When the data set was limited to individual stock investors whose total stock portfolio in any month in 2011 was above 5,000 TL (approximately USD 3,000), the number of investors was reduced to 432,085. Of these investors, 74,051 did not have any buy or sell transactions, in other words, they were dormant, during 2011[2]. In addition to the dormant investors, a portion of the remaining investors did had neither buy nor sell

[2]75% of the dormant investors are 50 years old or older and have been in the stock market for a relatively longer period of time. 66% of the dormant investors opened their accounts before 2002. Female investors constitute 41% of the dormant investors and 18% of the active investors.

transactions. These investors were also excluded from data set for further analysis. Hence, the data set was limited to those investors who had at least one buy and one sell transaction, resulting in 305,546 investors (labeled as the expanded investor set).

Table 1 displays both expanded and analysis investor set. Expanded investor set consists of buy and sell data of investors whose total stock portfolio in any month in 2011 was above 5,000 TL with at least 1 buy and sell transaction.

Table 1. Transaction Data for Expanded Investor Set and Analysis Investor Set

	Expanded Investor Set	Analysis Investor Set
Number of Investors	305,546	244,146
Number of Buys	92,560,232	31,563,471
Total Value of Buys (m TL)	519,154	148,199
Mean Buy Value	5,609	4,695
Median Buy Value	790	990
Standard Deviation Buy	21,587	19,516
Number of Sells	92,238,569	31,433,535
Total Value of Sells (TL)	516,590	145,822
Mean Sell Value	5,601	4,639
Median Sell Value	770	865
Standard Deviation Sell	20,679	16,891

Table 1 shows that the total trading volume of the expanded investor set is 517.9 billion TL (buy and sell amounts divided by two), constituting 76% of the total trading volume in the ISE in 2011, indicating that the sample has significant influence on price formation in the stock market. 15% of the remaining trading volume can be attributed to foreign investors and the rest to low portfolio value individual Turkish stock investors (investors with monthly average stock portfolio values lower than 5,000 TL in 2011) and local institutional investors. However, a portion of these investors have very high annual

turnover values at millions levels, some have as high as 10 billion[3]. One possible explanation is that these high turnover investors have their wealth managed by professional money managers, or they act like day traders and scalpers. For this reason, these investors were excluded. In the analyses, turnover value is capped at 100 in comparison with international benchmarks. In addition, according to the ISE and CRA, the average holding period of individual investors is around 30 days, implying an annual turnover of 12. The mean turnover is 11.2 when it is capped at 100. If cut off is changed (up to 1,000), results do not change. Moreover, the main results do not change when high turnover investors are included in the analysis using the natural logarithm of turnover. Hence, turnover is capped at 100, decreasing the sample size to 244,146 investors (labeled as the analysis investor set).

Thus, the analysis investor set consists of buy and sell data of investors whose total stock portfolio in any month in 2011 was above 5,000 TL with at least 1 buy and sell transaction, excluding abnormally high turnover investors (investors who shift their portfolios more than 100 times annually).

Demographics of high turnover investors (investors with turnover higher than 100) are slightly different. Compared to analysis investor set, high turnover investors are mostly male (88% versus 83%), younger (investors up to 35 years old are 21% versus 27%), not as wealthy (investors with wealth up to 10,000 TL – approximately USD 6,000 – are 41% versus 34%) and more experienced (account open date 2002 or earlier

[3]Median turnover is 7 where as mean turnover is 1.15m and standard deviation is 278m, implying high dispersion.

49% versus 36%).[4] There is no difference in terms of the region of residence. However, as expected, investors with high turnover have significantly more buy and sell transactions than those in analysis data set. 12% of high turnover investors have 1,000 or more buys and sells (versus 2% in analysis investor set). Investors with 1.5m TL (approximately USD 800 thsd) or higher total value of buys and sells constitute 20% of high turnover investors (versus 6% in analysis investor set).

Table 1 shows that the total trading volume of the analysis investor set is 147.0 billion TL, which was 22% of the total trading volume in the ISE in 2011. The investors made 31.6 million buy transactions that were worth 148.2 billion TL and 31.4 million sell transactions that were worth 145.8 billion TL. Average buy value was 4,695 TL (median 990 TL), slightly higher than average sell value of 4,639 TL (median 865 TL).

Table 2 displays the demographics of 244,146 investors in the analysis investor set. Age is the age of investor in 2011. Wealth is the average of 12 end-of-month portfolios consisting of equity, funds, warrants and corporate bonds. Experience is the account open date of the investor (if more than one accounts were available, the opening date of oldest account was taken into consideration). Region is the geographical region of residence of investor registered in CRA database. N/A indicates data was not available.

[4]GDP per capita in Turkey is USD 10,469 in 2011

Table 2. Investor Demographic Data

			N	%	Cum. %
Gender	1	Male	203,051	83%	83%
	2	Female	41,095	17%	100%
Age	1	25<	3,412	1%	1%
	2	25-29	19,600	8%	9%
	3	30-34	42,013	17%	27%
	4	35-39	46,719	19%	46%
	5	40-44	40,633	17%	62%
	6	45-49	31,278	13%	75%
	7	50-54	23,759	10%	85%
	8	55-59	16,273	7%	92%
	9	60≥	20,459	8%	100%
Wealth	1	100-1,000	2,704	1%	1%
	2	1,000-5,000	38,176	16%	17%
	3	5,000-10,000	43,212	18%	34%
	4	10,000-20,000	47,745	20%	54%
	5	20,000-50,000	54,004	22%	76%
	6	50,000-100,000	27,117	11%	87%
	7	100,000-250,000	18,935	8%	95%
	8	250,000-500,000	6,607	3%	98%
	9	500,000-1,000,000	3,085	1%	99%
	10	1,000,000-5,000,000	2,170	1%	100%
	11	5,000,000+	391	0%	100%
Experience	1	After 2008	24,877	10%	10%
	2	2006-2008	53,744	22%	32%
	3	2003-2005	76,671	31%	64%
	4	2000-2002	43,434	18%	81%
	5	Before 2000	45,420	19%	100%
Region		N/A	816	0%	0%
		Aegean	36,321	15%	15%
		Black Sea	17,749	7%	22%
		Central Anatolia	40,657	17%	39%
		East Anatolia	6,919	3%	42%
		Marmara	109,948	45%	87%
		Mediterranean	24,095	10%	97%
		Southeast Anatolia	7,641	3%	100%

For confidentiality reasons, CRA provided categorized data for age, experience and wealth. Male investors are 83% of the total investor base, whereas the 30-55 age

group accounts for 76% of all investors. 76% of the investors have wealth of 50,000 TL or less and 90% of the investors opened their accounts before 2008 (three or more years of investment experience in stock exchange). Almost half of the investors (45%) reside in Marmara Region, mostly in Istanbul, which is the largest city in Turkey. Next is Central Anatolia with 17%, mainly Ankara, which is the second largest city, followed by the Aegean region (15%), mainly İzmir, the third largest city. The Marmara region is the most developed and Southeast Anatolia region is the least developed among the regions in terms of welfare, income and education.

Stock market performance in 2011 was slightly bearish. The ISE100 index, which consists of the largest 100 companies, decreased from 67,608 at the beginning of the year to 51,267 at year end. However, out of 253 trading days, the ISE100 index had positive returns on 129 days and negative returns on 124 days.

Methodology

Overconfidence

Using a theoretical model, Harris and Raviv (1993) show that differences in opinions lead to trading among investors. Hence, trading volume is related to different expectations among investors. Differences in opinions are a result of different interpretations of the same signal by investors. As they rely more on their beliefs and decisions, overconfident investors' interpretations of the same signal will significantly differ from those of rational investors. This difference may cause the increased trading volume for overconfident investors. De Bondt and Thaler (1995) state that the key behavioral factor in understanding the trading puzzle is overconfidence. Kyle and Wang (1997) and Benos (1998) argue that overconfident investors trade more aggressively

because they believe that they have better information. Kahneman and Riepe (1998) propose that overconfidence should be expected from those who do not face similar problems every day, or who make explicitly probabilistic estimates and obtain feedback on outcomes of their decisions, implying that individual stock investors are likely to be overconfident.

Odean (1998a) develops a theoretical model in which overconfident investors overestimate the precision of their knowledge about the value of an asset. These investors overestimate the probability that their personal assessment of an asset's value is more accurate than that of others. Thus, overconfident investors believe their valuations to be correct which increases the differences in opinions among individual investors. The author proposes that that trading volume increases when investors are overconfident. Odean (1999) tests this hypothesis using data provided by a discount brokerage house in the USA. He argues that if traders are overconfident in the precision of information, then the average return of the securities they sell must outperform the average return of the securities they buy. He finds that the average return of the securities sold outperform the average return of the securities purchased over the horizons of four months, one year and two years. He looks for possible explanations to excessive trading resulting in losses and eliminates meeting liquidity needs, realizing tax losses and rebalancing the portfolio or moving to a less risky portfolio. He concludes that excessive trading resulting in losses may be due to overconfidence. A number of studies also confirm that overconfident investors trade more. An incomplete list of these papers includes Barber and Odean (1999, 2000, 2001, 2002), Hirshleifer and Luo (2001), Gervais and Odean (2001), Chuang and Lee (2006), Statman et al. (2006),

Glaser and Weber (2007), Graham et al. (2009), Glaser and Weber (2009), Grinblatt and Keloharju (2009), and Hoffmann et al. (2010).

Similar to Barber and Odean (2001), annual turnover is used to measure overconfidence. Annual turnover is twelve times the average monthly turnover. For each month, monthly turnover is calculated based on the following formula.

$$Monthly\ Turnover_t = \frac{\frac{\sum_{i=1}^{n} X_{it} * P_{it}}{W_t}}{2}$$

where X_{it} is the amount of stock i purchased or sold in month t, P_{it} is the beginning of the month price of the stock purchased or sold and W_t is the total stock portfolio value of the investor at the beginning of the month. Higher turnover implies higher overconfidence. Since both theoretical and empirical findings for turnover are robust, it is used as the main proxy to measure overconfidence.

Josephs et al. (1992) argue that low self-esteem individuals take less risk than high self-esteem individuals. As Campbell (1990) shows, high self-esteem people have higher confidence. Hence, it can be inferred that overconfident investors tend to take more risk. Chuang and Lee (2006) find that overconfident investors trade more in riskier securities. They measure riskiness of a security as return volatility and firm specific risk (return volatility minus market component). Glaser and Weber (2009) also argue that overconfident investors buy high risk stocks. These findings imply that overconfidence can also be measured using portfolio riskiness. Consistently, two different measures are used as proxies of portfolio riskiness. The first measure is the percentage of stocks from the ISE30 since these stocks have high market capitalization and high liquidity; they are thus assumed to be less risky. The second measure is the percentage of small market

capitalization stocks in the portfolio as the literature also suggests, small stocks are riskier. Moreover, the average return volatility of ISE30 stocks was smaller and that of small market capitalization stocks were larger than rest of the stocks during 2009-2011. Hence, taking also return volatility into account, ISE30 stocks turned out to be less risky and small company stocks turn out to be more risky.

The ISE30 ratio is the twelve-month average of the monthly ISE30 ratio. The monthly ISE30 ratio is calculated based on the month-end portfolios.

$$Mothly\ ISE30\ Ratio_t = \frac{ISE30\ stocks\ in\ the\ portfolio}{Total\ stocks\ in\ the\ portfolio}$$

A lower ISE30 ratio implies riskier portfolios. For example, if stocks A and B are in the ISE30, and a portfolio consists of stocks A, B and C, then the ISE 30 ratio is 67%.

Likewise, small Mcap ratio is twelve-month average of monthly small Mcap ratio. Monthly small Mcap ratio is calculated based on month-end portfolios.

$$Monthly\ Small\ Mcap\ Ratio_t = \frac{Small\ Mcap\ stocks\ in\ the\ portfolio}{Total\ stocks\ in\ the\ portfolio}$$

A higher small Mcap ratio implies riskier portfolios. Firms with market capitalization lower than USD 100m are labeled as small. As of the end of 2011, almost 50% of the stocks had market capitalizations lower than USD 100m. The maximum market capitalization value was USD 13,119m.

Heath and Tversky (1991) use the competence hypothesis and argue that overconfident investors may forego the advantage of diversification and concentrate on a small number of companies with which they are more familiar. Odean (1998a) finds that overconfident traders hold under-diversified portfolios. Similarly, Goetzmann and

Kumar (2008) find that high portfolio turnover, which is a sign of overconfidence, is related to under-diversification. The authors argue that more overconfident investors hold under-diversified portfolios similar to the investors with a tendency towards local stocks, in other words, the investors with familiarity bias. Glaser and Weber (2009) argue that with increased portfolio turnover individuals reduce the number of stocks in their portfolio. These findings imply that overconfidence can be measured using diversification. In line with the literature, average number of stocks in the portfolio is used as a naïve way of measuring the diversification level.

Table 3 presents the correlations among proxies for overconfidence. Turnover is negatively correlated to the ISE30 ratio and diversification and is positively correlated to the small Mcap ratio. The small Mcap ratio is by definition negatively correlated to the ISE30 ratio and not to diversification. Correlation of diversification with other overconfidence proxies is either low or insignificant.

Table 3. Correlation of Overconfidence Proxies

	Turnover	ISE30	Diversification
ISE30	-0.128***		
Diversification	-0.052***	0.002	
Small Mcap	0.114***	-0.477***	0.007***

*** indicates statistically significant at 1%

Familiarity Bias

Odean (1999) suggests that securities that have performed unusually poorly or unusually well are more likely to be discussed in the media, more likely to be considered by

individual investors and as a result more likely to be purchased. He finds that the investors tend to buy securities that have risen or fallen more over the previous six months than the securities they sell. Gervais et al. (2001) find that stocks experiencing high trading volume over a day or week tend to appreciate over the following month. Hirshleifer et al. (2008) use transaction data of individual investors from a brokerage house and find that investors are net buyers after both negative and positive extreme earnings surprises, consistent with an attention effect. Barber and Odean (2008) argue that the buying behavior of individual investors is heavily influenced by stocks that draw their attention. They use stock news in the media, unusual trading volume and extreme return as proxies for attention grabbing factors. They find that abnormal trading volume is the best indicator of attention while return and news metric follow abnormal trading volume. These findings imply that familiarity bias can be measured by looking at the relation between stock purchases and factors increasing familiarity towards these stocks. The more the investor is exposed to the stock, the more familiar he or she becomes.

From this standpoint, previous ownership is expected to be a good measure for familiarity bias. After an investor buys a stock, the stock becomes more familiar. If a stock was previously purchased by the investor in 2011 or the stock was in the portfolio at the beginning of the year, the transaction is flagged. Previous ownership ratio is calculated using the following formula:

$$Previous\ Ownership\ Ratio = \frac{Flagged\#\ of\ buy\ transactions}{Total\ \#\ of\ buy\ transactions}$$

Higher previous ownership ratio indicates higher familiarity bias. Previous ownership ratio is used as the main proxy to measure familiarity bias as it is the most direct indicator of familiarity with a stock.

Alternative definitions of familiarity bias measures from the literature are also used for robustness checks. In line with Barber and Odean (2008), extreme returns can also be used to measure familiarity bias. If the absolute value of the previous day's return of stock divided by previous day ISE100 (index composed of largest 100 companies in the ISE) return is above 125%, the purchase transaction is flagged as an absolute abnormal return buy. This cut off point is determined based on the absolute return of stocks and ISE100. In 2011, the average of the mean absolute return of stocks was 2.03%, whereas mean absolute return of the ISE100 was 1.27%. The absolute abnormal return ratio is calculated using the following formula:

$$Absolute\ Abnormal\ Return\ Ratio = \frac{Flagged\#\ of\ buy\ transactions}{Total\ \#\ of\ buy\ transactions}$$

A higher ratio indicates higher familiarity bias.

As presented in Barber and Odean (2008), abnormal trading volume can also be used to measure familiarity bias. If the value of the previous day's volume change (vs. 2 days ago) of the stock divided by the previous day's ISE100 volume change (vs. 2 days ago) is above 150%, the purchase transaction is flagged as an abnormal volume buy. Abnormal volume ratio is calculated using the following formula:

$$Abnormal\ Volume\ Ratio = \frac{Flagged\#\ of\ buy\ transactions}{Total\ \#\ of\ buy\ transactions}$$

A higher ratio indicates higher familiarity bias.

Table 4 shows the correlation of proxies for familiarity bias. Correlation among familiarity bias proxies is either insignificant or too low.

Table 4. Correlation of Familiarity Bias Proxies

	Previous Ownership	Abs Abn Return
Abs Abn Return	0.000	
Abn Volume	-0.003	0.005***

*** indicates statistically significant at 1%

Representativeness Heuristic

Chan et al. (2004) argue that the representativeness heuristic may lead investors to extrapolate past performance of assets into the future and thus set prices too low or too high, which in turn generates return reversals. Chen et al. (2007) use transaction data of a large Chinese brokerage house to analyze representativeness heuristic among Chinese investors. The authors use extrapolation as a form of representativeness heuristic. They find that the 4-month prior performance of stocks purchased is surprisingly high, whereas the past 1-year return is almost normal. Barber et al. (2009) use extrapolation as a form of representativeness heuristic and measure 3-year prior market adjusted return of stocks purchased by individual investors. The authors find that individual investors buy stocks with strong past returns. This relation peaks at 1-year prior to purchase and goes back to 3 years prior to purchase. Bildik and Gülay (2007) find that individual Turkish stock investors are more myopic. Hence, a shorter time period is employed than the ones used by Barber et al. (2009).

For each buy transaction, positive return ratio is calculated as the number of days in which stock has a market (ISE100) adjusted positive return in the last 150 trading days prior to the purchase date divided by number of days stock is traded in the same period. For each investor, a 150-day positive return trend is the average positive return ratio for all purchases. The representativeness heuristic is also measured for the last 30 and 90 trading days prior to the purchase date using the same calculation methodology for robustness checks.

Table 5 shows the correlation of proxies for representativeness heuristic. Correlations are statistically significant, positive and high.

Table 5. Correlation of Representativeness Heuristic Proxies

	150 Day Return	90 Day Return
90 Day Return	0.874***	
30 Day Return	0.600***	0.739***

*** indicates statistically significant at 1%

Status Quo Bias

Status quo bias is related to doing nothing or maintaining current decisions, implying that status quo bias involves reluctance to trade. Hence, individuals exhibiting status quo bias are expected to keep their current portfolios unchanged. The more the portfolio of an investor changes, the more decisions he/she takes, implying a lower degree of status quo bias. Using all buy and sell transactions in 2011, constructed end-of-day portfolios for each investor. For a particular day t, daily portfolio percentage change is calculated using the following formula.

$$Portfolio\ Percentage\ Change_t = Avg\left\{\sum_{i=1}^{n} \frac{Abs(X_{it} - X_{it-1})}{X_{it-1}}\right\}$$

where X_i is the number of i_{th} stock in the portfolio.

Portfolio percentage change is the annual average portfolio percentage change for all days. Since the portfolio percentage change measures the daily level of change in a portfolio, higher values indicate lower status quo bias. For example, suppose on day 1, a portfolio consists of two A and four B stocks and suppose on day 2, the portfolio consists of four A, two B and two C stocks, the daily percentage change in the portfolio is 67% (50% change in A, 50% change in B and 100% change in C divided by three, representing number of stocks A, B, C).

Disposition Effect

Odean (1998b) uses the purchase price as the reference price to determine winners and losers. He compares the sales price of each stock sold to its average purchase price to determine whether the stock is sold for a gain or loss. He considers each stock that is in the portfolio at the beginning of that day, but not sold, as a paper (unrealized) gain or loss (or neither). Paper gains or losses are determined by comparing the stock's high and low prices for that day to its average purchase price. If both daily high and low are above (below) the average purchase price, it is counted as a paper gain (loss). If the average purchase price lies between daily high and low, it is neither a gain nor a loss. On days when no sales take place in an account, no gains or losses (realized or paper) are counted. Odean defines Proportion of Gains Realized (PGR) as realized gains divided by the sum of realized gains and paper gains, and Proportion of Losses Realized (PLR) as realized losses divided by the sum of realized losses and paper losses. Disposition Effect

is calculated to be the difference between PGR and PLR. A positive difference between PGR and PLR indicates that investors are more willing to realize gains. Barber and Odean (1999), Brown et al. (2006), Dhar and Zhu (2006), Barber et al. (2007), Chen et al. (2007) and Barber et al. (2009) use the same methodology in their disposition effect studies.

A methodology similar to Odean's (1998b) is used in this thesis to measure disposition effect. With a backward looking approach (for each investor starting from last trading day of 2011 and going back to beginning of 2011), each sell transaction is paired with one or more buy transactions (depending on the amount of stocks sold). Then, it is determined if the sell is a gain or loss by comparing the sell price with the purchase price. If there are more than one buy transactions for matching, the average purchase price is used as the reference price. For each day a sell transaction takes place, realized gain (or loss) for the sell transaction and paper gain (or loss) for the stocks not sold in that particular day is calculated. Disposition effect is calculated using the following formula.

$$Disposition\ Effect = \frac{PGR}{PLR}$$

where

$$PGR\ (proportion\ of\ realized\ gains) = \frac{\#\ \text{of realized gains}}{\#\ \text{of realized gains} + \#\ \text{of paper gains}}$$

$$PLR\ (proportion\ of\ realized\ losses) = \frac{\#\ \text{of realized losses}}{\#\ \text{of realized losses} + \#\ \text{of paper losses}}$$

Figures higher than one indicate that the investor exhibits disposition effect whereas figures smaller than one indicate just the opposite.

Regression Analysis

For each bias, a regression analysis is run to determine how each demographic factor affects the behavioral bias.

$$Bias = \alpha Age + \beta Male + \gamma Experience + \delta_1 Wealth_Low + \delta_2 Wealth_High + \theta_1 Marmara + \theta_2 Southeast$$

In this regression model, Bias is overconfidence, familiarity bias, representativeness heuristic, status quo bias or disposition effect. Age is the age of the investor and is a continuous variable. Male is a dummy variable for gender, which equals one for male investors. Experience is the year the account was opened and is a continuous variable. Wealth_Low is a dummy variable, which equals one for wealth levels up to 10,000 TL and Wealth_High is a dummy variable and is equal to one for wealth levels higher than 100,000 TL. Marmara is a dummy variable, which equals one for the Marmara (most developed) region and Southeast is a dummy variable, which equals one for the Southeast Anatolia (least developed) region. Turnover, previous ownership ratio, 150 day positive return trend, portfolio percentage change and PGR/PLR are used as main measures of overconfidence, familiarity bias, representativeness heuristic, status quo bias and disposition effect, respectively. Other proxies such as the ISE30 ratio, the small Mcap ratio and the absolute abnormal return ratio are also used for robustness checks.

Since explanatory variables are categorical, three additional regression models have been utilized for robustness checks. In these models, wealth is a dummy which

equals one either for each wealth level presented in Table 2 or for low and high wealth levels presented above and experience is either continuous or is a dummy variable which equals one for each experience level presented in Table 2. However, for brevity, the results of these regressions are not presented in this thesis.

Return calculations are based on paired sell-buy transactions. Pairing is the same as the one discussed in measuring disposition effect. With a backward-looking approach (for each investor starting from the last trading day of 2011 and going back to the beginning of 2011), each sell transaction is paired with one or more buy transactions (depending on the amount of stocks sold). If there are more than one buy transactions for matching, the average purchase price is used as the reference price. For each investor, return is the weighted average of return of each paired buy-sell transactions.

CHAPTER 4

RESULTS

This chapter presents the results regarding how common the behavioral biases are, how demographics factors affect these biases, the relationship between biases, and the relationship between trade performance and biases.

Overconfidence

In line with literature, turnover is the main measure to analyze overconfidence. ISE30 ratio, small Mcap ratio and diversification are used as robustness checks.

Turnover

Turnover is twelve times the average monthly turnover, which is simply the rate of change in the beginning-of-month portfolio. Table 6 shows the descriptive statistics for turnover.

Table 6. Descriptive Statistics for Turnover

	N	Min	Max	Mean	Median	Std. Dev.
Turnover	244,146	0	100	11.23	4.29	17.16

The mean annual turnover equals 11.2 and the median equals 4.3. Both the mean and the median turnover levels are high compared to those described in the literature. Barber and Odean (2001) find that the mean turnover for a subset of US investors is 0.77 for men and 0.53 for women, implying that individual Turkish stock investors have a higher turnover than US investors. Chen et al. (2007) find that for Chinese investors, the

mean turnover is 3.27, significantly higher than US investors, yet still lower than Turkish investors, revealing that individual investors exhibit overconfident behavior.

The mean annual turnover, including the investors with turnover levels higher than 100, increases to 1.15 million, which is extremely high for a typical individual investor. One possible explanation for these investors with high turnover values is that they have their wealth managed by professional money managers or they act like day traders and scalpers: they are therefore excluded. In the analyses, turnover value is capped at 100 in comparison with international benchmarks. In addition to this, according to the ISE and CRA, the average holding period of individual investors is around 30 days, implying an annual turnover of 12. The mean turnover is 11.2 when turnover is capped at 100. Both the standard deviation in Table 6 and the histogram in Fig. 4 confirm that turnover is highly dispersed.

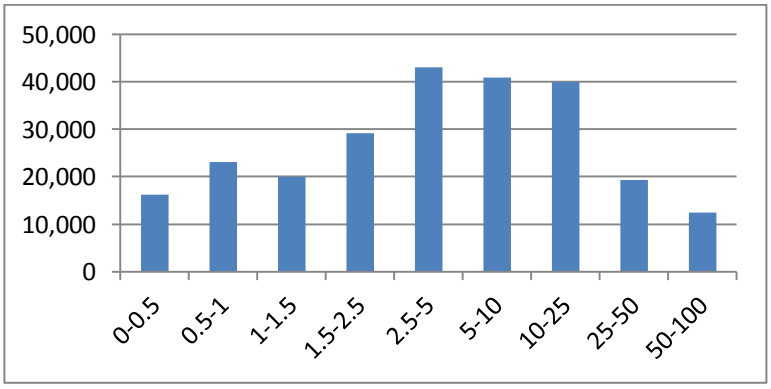

Fig. 4 Turnover histogram

Table 7 shows the mean turnover for each category. Table 8 reports the regression results.

Table 7. Mean Turnover for Each Demographic Breakdown

		Turnover
	Total	11.23
Gender	Male	11.86
	Female	8.10
Experience	After 2008	11.85
	2006-2008	11.35
	2003-2005	10.98
	2000-2002	11.36
	Before 2000	11.02
Age	25<	10.72
	25-29	11.84
	30-34	12.30
	35-39	12.09
	40-44	11.80
	45-49	11.06
	50-54	10.34
	55-59	9.43
	60≥	8.10
Wealth	100-1,000	7.47
	1,000-5,000	12.75
	5,000-10,000	12.17
	10,000-20,000	11.76
	20,000-50,000	10.80
	50,000-100,000	10.05
	100,000-250,000	9.50
	250,000-500,000	9.33
	500,000-1M	8.96
	1M-5M	8.61
	5M+	6.55
Region	N/A	9.97
	Aegean	11.06
	Black Sea	11.38
	Central Anatolia	11.42
	East Anatolia	13.00
	Marmara	10.77
	Mediterranean	11.96
	Southeast Anatolia	13.40

Table 8. Regression Results for Turnover

	Turnover
Constant	
Age	-0.058*** (-25.1)
Male	0.075*** (37.1)
Experience	0.027*** (11.5)
Wealth_Low	0.027*** (12.4)
Wealth_High	-0.025*** (-11.9)
Marmara	-0.016*** (-7.6)
Southeast	0.013*** (6.3)
Obs	244,146
R^2	0.014
Adjusted R^2	0.014

*** indicates coefficient is significant at 1%. t values in parentheses.

Dependent variable is annual turnover and independent variables are age, gender (in the form of male dummy), experience, wealth (in the form of dummy variables for low and high wealth categories) and geographical region of residence (in the form of dummy variables for Marmara and Southeast Anatolia regions). Wealth_Low is dummy for portfolio value less than 10,000 TL and Wealth_High is dummy for portfolio value above 100,000 TL.

The coefficient on age is negative and statistically significant, suggesting that overconfident behavior decreases with age. However, as Table 7 shows, the effect of age is non-monotonic; age has a positive effect on overconfidence up to the 30-34 age group,

but has a negative effect for the higher age groups. The nonlinear relationship is also confirmed by the quadratic age term in the regression, which is omitted for brevity. Male investors exhibit more overconfidence than female investors, which confirms the vast majority of findings in the literature. On the other hand, experience increases overconfident behavior, contrary to expectations. However, this finding is valid only for low wealth investors and experience decreases overconfidence for high wealth investors. One possible explanation is the definition of experience. The account opening date does not necessarily measure experience. An investor may gain experience in a shorter period of time with frequent trading. However, when an alternative definition of experience is used which is the number of years after the first time the investor's stock portfolio reaches 5,000 TL, our results do not change. When the effect of wealth on turnover is considered, the coefficient on wealth is negative and statistically significant suggesting that wealth decreases overconfidence. However, as Table 7 shows, the only exception is the lowest wealth group, which has the second lowest turnover among all wealth categories. This is probably mainly due to low amount of available funds to trade. Wealth may be related to financial sophistication as wealthy investors have better access to information and can leverage on professional portfolio management. Investors in the Marmara region have lower overconfidence, whereas investors in the Southeast Anatolia region have higher overconfidence. The turnover difference between the two regions is not related to gender, age, experience or wealth. The Marmara region is economically more developed than the Southeast Anatolia region. Besides this, the percentage of university graduates is higher in the Marmara region (13% versus 6% in the Southeast

Anatolia region).[5] Therefore, financial sophistication in the Marmara region is more likely to be higher than that in the Southeast Anatolia region. Overall, wealth and region imply that sophisticated investors are less prone to overconfidence.

Findings of behavioral finance literature shows that behavioral biases may have a negative impact on the trade performance of investors. To analyze the relationship between trade performance and biases, the return for each sell transaction is calculated. For 7% of the investors, return is not calculated since no buy-sell matching is possible. Table 9 shows that the mean return for the remaining 93% of investors is 1.37%, whereas the average daily return of the ISE100 in 2011 is -0.10%. Although the average daily performance of the ISE100 is lower, 43% of the investors have negative returns.

Table 9. Mean Return for Turnover

	Return	Total	1st Quartile Lowest 25%	2nd Quartile	3rd Quartile	4th Quartile Highest 25%
Turnover	Mean	1.37%	2.79%	2.03%	0.92%	0.12%
	Median	0.56%	2.29%	1.87%	0.62%	-0.14%
	Std. Dev.	10.87%	17.81%	11.94%	6.52%	4.21%

Table 9 shows the negative relationship between return and turnover. The mean return in the lowest quartile of turnover is 2.79% and is significantly higher compared to that of the highest quartile, which is 0.12%. The mean return for analysis investor set is 1.37% with a median of 0.56%. Although not presented here, the mean return of investors with turnover higher than 100 is 0.35% with a median of -0.07%. Moreover, Table 10 shows that men have a lower return than women, 1.18% versus 2.36%.

[5]Based on Turkish Statistical Institute data

Table 10. Mean Return for Each Demographic Breakdown

		Return
	Total	1.37%
Gender	Male	1.18%
	Female	2.36%
Experience	After 2008	0.57%
	2006-2008	0.94%
	2003-2005	1.45%
	2000-2002	1.63%
	Before 2000	2.00%
Age	25<	1.02%
	25-29	0.48%
	30-34	0.81%
	35-39	1.13%
	40-44	1.33%
	45-49	1.76%
	50-54	1.90%
	55-59	2.17%
	60≥	2.47%
Wealth	100-1,000	-0.52%
	1,000-5,000	-0.24%
	5,000-10,000	0.59%
	10,000-20,000	1.28%
	20,000-50,000	1.94%
	50,000-100,000	2.45%
	100,000-250,000	2.86%
	250,000-500,000	3.04%
	500,000-1M	2.89%
	1M-5M	3.37%
	5M+	3.57%
Region	N/A	1.49%
	Aegean	1.38%
	Black Sea	1.36%
	Central Anatolia	1.44%
	East Anatolia	0.54%
	Marmara	1.51%
	Mediterranean	1.11%
	Southeast Anatolia	0.54%

Hence, in line with the literature, it is found that trading is hazardous to wealth and that men's trading performance is worse than women's due to men's higher turnover levels.

Robustness Checks

In order to check the robustness of the findings, alternative variable definitions, subsamples and regressions are experimented. Findings of the analyses are virtually unchanged when these alternatives are used.

First, the ISE30 ratio, the small Mcap ratio and diversification are used as alternative proxies for overconfidence. Table 11 shows the descriptive statistics for alternative proxies.

Table 11. Descriptive Statistics for Overconfidence Alternative Proxies

ISE 30	N	Min	Max	Mean	Median	Std. Dev.
	244,146	0	1.00	0.30	0.16	0.34

Small Mcap	N	Min	Max	Mean	Median	Std. Dev.
	244,064	0	1.00	0.28	0.22	0.27

Diversification	N	Min	Max	Mean	Median	Std. Dev.
	244,146	0	347.3	3.43	2.00	5.93

On average, individual investors' portfolio consists of 30% ISE30 stocks and 28% small Mcap stocks. A typical investor holds 3.43 different stocks in the portfolio.

Table 3 shows that turnover is negatively correlated to the ISE30 ratio and diversification and positively correlated to the small Mcap ratio. Small Mcap ratio is by definition negatively correlated to the ISE30 ratio and not to diversification. Correlation

of diversification with other proxies is either low or insignificant, implying that diversification is not as good as other proxies in measuring overconfidence, or does not necessarily measure overconfidence. Hence, further regression analysis for overconfidence robustness checks is based on portfolio riskiness (measured by the ISE30 ratio and small Mcap ratio). Table 12 shows regression results for the ISE30 and the small Mcap.

Table 12. Regression Results for Overconfidence Using Alternative Proxies

	ISE30	Small Mcap
Constant		
Age	0.106*** (45.8)	-0.085*** (-36.5)
Male	-0.046*** (-22.7)	0.047*** (23.3)
Experience	-0.003 (-1.3)	0.011*** (4.6)
Wealth_Low	-0.007*** (-3.4)	0.017*** (8.0)
Wealth_High	0.056*** (26.4)	-0.061*** (-28.8)
Marmara	0.021*** (10.5)	-0.037*** (-18.2)
Southeast	-0.006*** (-3.0)	0.009*** (4.5)
Obs	244,146	244,064
R^2	0.021	0.019
Adjusted R^2	0.021	0.021

*** indicates coefficient is significant at 1%. t values in parentheses.

Dependent variable is the ISE30 ratio and Small Mcap ratio. Independent variables are age, gender (in the form of male dummy), experience, wealth (in the form of dummy variables for low and high wealth categories) and geographical region of residence (in

the form of dummy variables for Marmara and Southeast Anatolia regions). Wealth_Low is dummy for portfolio value less than 10,000 TL and Wealth_High is dummy for portfolio value above 100,000 TL. Regression results for the ISE30 ratio and small Mcap ratio in line with those of turnover.

Additional analyses are also carried out to confirm to check the findings. High turnover investors (after transforming to natural logarithm) are included into the turnover regression for robustness checks. Different sub samples including male only, female only, low / high age, low / high experience, and low / high wealth regressions are also used for further robustness checks. Alternative regression models (categorical versus continuous explanatory variables) are employed for additional checks. Although not presented for brevity, all these robustness checks confirm the main findings.

Familiarity Bias

Previous ownership ratio is the primary measure, absolute abnormal return ratio and abnormal volume ratio are used as robustness checks.

Previous Ownership Ratio

Previous ownership ratio calculates the ratio of buy transactions that the investor has prior information because either the investor has purchased the stock previously in 2011 or has the stock in the portfolio at the beginning of 2011. Table 13 shows that the mean previous ownership ratio is 0.49 (median 0.53).

Table 13. Descriptive Statistics for Previous Ownership Ratio

	N	Min	Max	Mean	Median	Std. Dev.
Previous Ownership Ratio	244,146	0	0.99	0.49	0.53	0.27

The histogram in Fig. 5 shows that 58% of investors have 50% or higher previous ownership ratio.

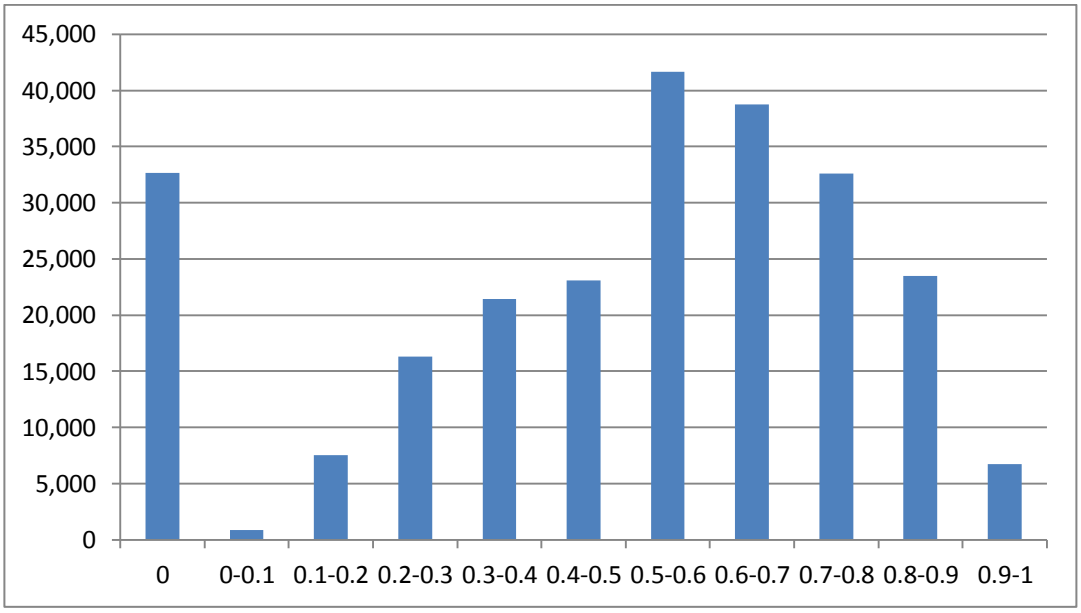

Fig. 5 Previous ownership ratio histogram

These findings imply that individual Turkish equity investors are inclined to purchase stocks that they are familiar with.

Table 14 shows the mean previous ownership ratio for each gender, age, wealth, experience and region category. Table 15 shows the regression results.

Table 14. Mean Previous Ownership Ratio for Each Demographic Breakdown

		Previous Ownership Ratio
	Total	0.492
Gender	Male	0.503
	Female	0.436
Experience	After 2008	0.477
	2006-2008	0.489
	2003-2005	0.487
	2000-2002	0.501
	Before 2000	0.502
Age	25<	0.463
	25-29	0.489
	30-34	0.505
	35-39	0.505
	40-44	0.501
	45-49	0.492
	50-54	0.478
	55-59	0.471
	60≥	0.453
Wealth	100-1,000	0.344
	1,000-5,000	0.442
	5,000-10,000	0.464
	10,000-20,000	0.487
	20,000-50,000	0.507
	50,000-100,000	0.524
	100,000-250,000	0.543
	250,000-500,000	0.554
	500,000-1M	0.579
	1M-5M	0.618
	5M+	0.696
Region	N/A	0.476
	Aegean	0.484
	Black Sea	0.483
	Central Anatolia	0.503
	East Anatolia	0.511
	Marmara	0.485
	Mediterranean	0.505
	Southeast Anatolia	0.521

Table 15. Regression Results for Previous Ownership Ratio

	Previous Ownership Ratio
Constant	
Age	-0.098*** (-42.5)
Male	0.087*** (43.3)
Experience	0.026*** (11.6)
Wealth_Low	-0.111*** (-51.8)
Wealth_High	0.080*** (38.0)
Marmara	-0.025*** (-12.5)
Southeast	0.012*** (6.0)
Obs	244,146
R^2	0.034
Adjusted R^2	0.033

*** indicates coefficient is significant at 1%. t values in parentheses.

Dependent variable is previous ownership ratio and independent variables are age, gender (in the form of male dummy), experience, wealth (in the form of dummy variables for low and high wealth categories) and geographical region of residence (in the form of dummy variables for Marmara and Southeast Anatolia regions). Wealth_Low is dummy for portfolio value less than 10,000 TL and Wealth_High is dummy for portfolio value above 100,000 TL.

The results are similar to those of overconfidence. Familiarity bias decreases with age. However, as Table 14 shows, age is nonlinearly related to previous ownership, increasing up to the 35-39 age group, and decreasing afterwards. Nonlinear relationship is also confirmed by quadratic age term in the regression (not presented here for

brevity). Male investors exhibit familiarity bias more than female investors. Experience increases familiarity bias, contrary to expectations. This is probably due to high correlation between age and experience (correlation 0.458). When age is omitted from the model, experience turns out to negatively and significantly affect familiarity bias. Age confounds with experience, as the interaction term between age and experience is statistically significant. Hence, age and experience may be measuring the same underlying factor affecting familiarity. Another possible explanation why experience positively affects familiarity bias is the definition of experience. The account opening date does not necessarily imply high experience. An investor may gain experience in a shorter period of time with high frequency trading. However, when alternative definition of experience is used, (the year when investor first reaches 5,000 TL stock portfolio) the results do not change. Wealth increases familiarity bias, contrary to expectations. However, the number of buy transactions is higher for wealthy investors. Due to the definition of previous ownership ratio, a higher buy transaction number implies a higher previous ownership ratio. Previous ownership ratio is positively correlated to the number of buy transactions (correlation 0.607) and the number of buy transactions is positively correlated to wealth (correlation 0.304). Hence, when the number of buy transactions is added as a control variable, wealth turns out to negatively affect familiarity bias. The negative effect of wealth on familiarity bias is also confirmed with the absolute abnormal return regression analysis presented in Table 18. Investors in the Marmara region have a lower familiarity bias, whereas investors in the Southeast Anatolia region have a higher familiarity bias. The difference between these two regions is not related to gender, age, experience or wealth. The Marmara region is economically more developed than the Southeast Anatolia region. Besides this, the percentage of university graduates

is higher in the Marmara region (13% versus 6% in the Southeast Anatolia region). As the findings in the relationship of overconfidence in wealth and region imply, financial sophistication may decrease familiarity bias.

There is a nonlinear relationship between return and previous ownership. Return is lowest among investors whose previous ownership ratio is zero. These investors also have the lowest number of buy and sell transactions. Hence, their performance may deteriorate overall relation with return. Excluding this group, the return decreases up to 0.8 previous ownership ratio level and increases afterwards. The nonlinear relation between return and turnover is further presented in Table 16.

Table 16. Mean Return for Previous Ownership Ratio

	Return	Total	1st Quartile Lowest 25%	2nd Quartile	3rd Quartile	4th Quartile Highest 25%
Previous Ownership Ratio	Mean	1.37%	1.95%	1.32%	1.28%	1.43%
	Median	0.56%	1.00%	0.47%	0.32%	0.58%
	Std. Dev.	10.87%	12.19%	9.84%	8.63%	7.60%

The return in the lowest quartile of familiarity bias is significantly different compared to the highest quartile. The results indicate that investors who trade with highly familiar stocks have a better performance. This may be due to information effect as investors possibly have more information regarding the stocks that they have frequently traded.

Robustness Checks

Absolute abnormal return and abnormal volume are alternative proxies for familiarity bias. Table 17 presents the descriptive statistics of these proxies.

Table 17. Descriptive Statistics for Familiarity Bias Alternative Proxies

Absolute Abnormal Return	N	Min	Max	Mean	Median	Std. Dev.
	244,146	0	1.00	0.59	0.60	0.21

Abnormal Volume	N	Min	Max	Mean	Median	Std. Dev.
	244,146	0	1.00	0.42	0.41	0.20

59% of the purchase transactions have previous day absolute abnormal return and 42% of the purchase transactions have previous day abnormal volume movements. Table 4 shows that previous ownership is not significantly correlated to absolute abnormal return and abnormal volume. Familiarity bias may stem from any attention-grabbing event among many such as the investor being an employee of the company, the investor living within the proximity of the company, the advertising and marketing efforts of the company, word of mouth, or any other stock or investor specific attention grabbing emotional or rational factor, all of which are hard to capture with one specific measure. Hence, it is difficult to find proxies to measure familiarity bias that confirm each other. Previous ownership is a direct indicator of familiarity. As a robustness check, although not significantly correlated, absolute abnormal return is used for further analysis as change in return is more likely to be attention grabbing compared to change in volume. Table 18 shows the regression results for the absolute abnormal return.

Table 18. Regression Results for Familiarity Bias Using Alternative Proxy

	Absolute Abnormal Return
Constant	
Age	-0.031*** (-13.4)
Male	0.005** (2.3)
Experience	-0.016*** (-7.0)
Wealth_Low	0.023*** (10.5)
Wealth_High	-0.029*** (-13.5)
Marmara	-0.006*** (-2.9)
Southeast	0.000 (0.1)
Obs	244,146
R^2	0.005
Adjusted R^2	0.005

*** and ** indicate coefficient is significant at 1% and 5% respectively. t values in parentheses.

Dependent variable is absolute abnormal return and independent variables are age, gender (in the form of male dummy), experience, wealth (in the form of dummy variables for low and high wealth categories) and geographical region of residence (in the form of dummy variables for Marmara and Southeast Anatolia regions). Wealth_Low is dummy for portfolio value less than 10,000 TL and Wealth_High is dummy for portfolio value above 100,000 TL. Regression results for absolute abnormal return are similar to those of previous ownership ratio.

Although for brevity they are not presented here, regression results are further confirmed using different robustness checks. The findings are similar for sub samples (male only, female only, low / high age, low / high experience, and low / high wealth

regressions). Findings are also robust for different regression models (using categorical vs. continuous explanatory variables). Furthermore, the results do not change when the expanded investor set (including high turnover investors) is used.

Representativeness Heuristic

150 trading day positive return trend is primary measure; 30 and 90 trading day positive return trend are used as robustness checks.

150 Trading Day Positive Return Trend

150 trading day positive return trend is the ratio of number of days in which stock has a market (ISE100) adjusted positive return in the last 150 trading days prior to purchase date divided by number of days the stock is traded in the same period. Table 19 shows that on average the mean 150 day positive return trend is 0.467 (median 0.465).

Table 19. Descriptive Statistics for 150 Trading Day Positive Return Trend

150 Trading Day Positive Return Trend	N	Min	Max	Mean	Median	Std. Dev.
	243,644	0	1	0.467	0.465	0.03

The histogram in Fig. 6 shows that 88% of the investors purchased stocks whose ISE100 adjusted returns in the last 150 trading day prior to purchase is positive between 40% and 50% of the time.

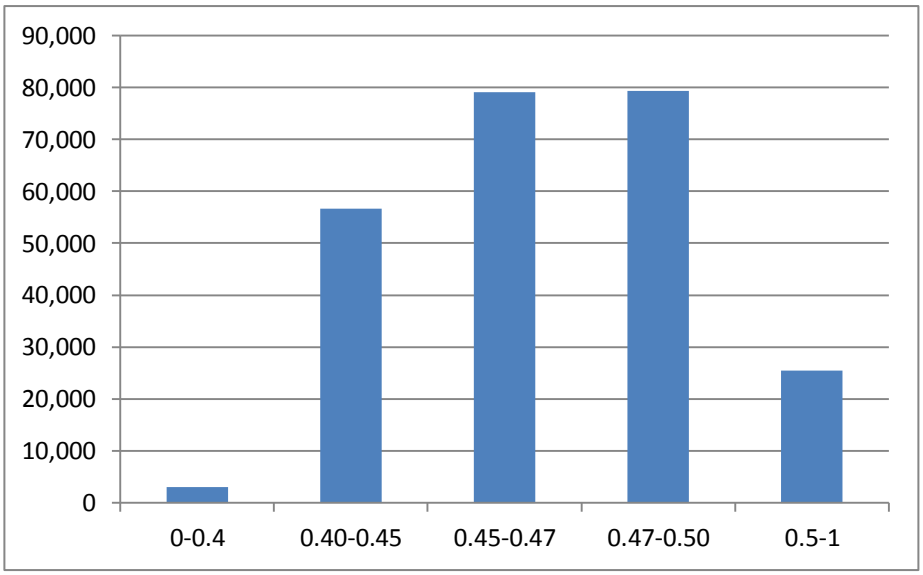

Fig. 6 150 trading day positive return trend histogram

These findings reveal that investors are not positive trend chasers, consistent with the findings of Bildik and Gülay (2007). Table 20 shows the mean 150 trading day positive return trend for each gender, age, wealth, experience and region category. Table 21 shows the regression results.

Table 20. Mean 150 Trading Day Positive Return Trend for Each Demographic Breakdown

		150 Trading Day Positive Return Trend
	Total	0.467
Gender	Male	0.466
	Female	0.470
Experience	After 2008	0.466
	2006-2008	0.466
	2003-2005	0.467
	2000-2002	0.466
	Before 2000	0.468
Age	25<	0.467
	25-29	0.466
	30-34	0.465
	35-39	0.465
	40-44	0.466
	45-49	0.466
	50-54	0.468
	55-59	0.469
	60≥	0.472
Wealth	100-1,000	0.464
	1,000-5,000	0.465
	5,000-10,000	0.466
	10,000-20,000	0.466
	20,000-50,000	0.466
	50,000-100,000	0.468
	100,000-250,000	0.469
	250,000-500,000	0.471
	500,000-1M	0.473
	1M-5M	0.475
	5M+	0.477
Region	N/A	0.466
	Aegean	0.466
	Black Sea	0.466
	Central Anatolia	0.466
	East Anatolia	0.464
	Marmara	0.468
	Mediterranean	0.464
	Southeast Anatolia	0.463

Table 21. Regression Results for 150 Trading Day Positive Return Trend

	150 Trading Day Positive Return Trend
Constant	
Age	0.053*** (22.9)
Male	-0.045*** (-22.4)
Experience	-0.014*** (-6.1)
Wealth_Low	-0.006*** (-2.7)
Wealth_High	0.033*** (15.2)
Marmara	0.042*** (20.5)
Southeast	-0.010*** (-5.1)
Obs	243,644
R^2	0.009
Adjusted R^2	0.009

*** indicates coefficient is significant at 1%. t values in parentheses.

The dependent variable is 150 trading day positive return trend and independent variables are age, gender (in the form of male dummy), experience, wealth (in the form of dummy variables for low and high wealth categories) and geographical region of residence (in the form of dummy variables for Marmara and Southeast Anatolia regions). Wealth_Low is dummy for portfolio value less than 10,000 TL and Wealth_High is dummy for portfolio value above 100,000 TL.

The results show that demographic factors affect representativeness heuristic just the opposite of the results they do for overconfidence. The representativeness heuristic increases with age. However, as Table 20 shows, age is nonlinearly related to representativeness heuristic, decreasing up to the 35-39 age group, and increasing

afterwards. The nonlinear relationship is also confirmed by the quadratic age term in the regression, which is not presented here for brevity. Women seem to chase positive returns more than men. This may be related to the fact that women are less overconfident than men and hence tend not to bear risk by investing in stocks recently underperforming. Experience decreases representativeness heuristic. However, the definition of experience may affect the outcome. The account opening date does not necessarily imply high experience. An investor may gain experience in a shorter period of time with high frequency trading. Yet, when alternative definition of experience is used (the year when investors first reaches 5,000 TL stock portfolio), the results do not change. Wealthy investors are more inclined to invest in stocks whose prices have recently increased. Investors in the Marmara region have a higher representativeness heuristic while the investors in the Southeast Anatolia region have a lower representativeness heuristic. The difference between these two regions is not related to gender, age, experience or wealth. The Marmara region is economically more developed than the Southeast Anatolia region. Besides this, the percentage of university graduates is higher in the Marmara region (13% versus 6% in the Southeast Anatolia region). Sophisticated investors seem to be more prone to the representativeness heuristic, just opposite to the case for overconfidence and familiarity bias.

Although our findings are statistically significant, because the means are very close to each other (as presented in Table 20), they are not economically significant. Table 22 shows the negative relation between return and representativeness heuristic.

Table 22. Mean Return for 150 Trading Day Positive Return Trend

	Return	Total	1st Quartile Lowest 25%	2nd Quartile	3rd Quartile	4th Quartile Highest 25%
150 Trading Day Positive Return Trend	Mean	1.37%	1.62%	1.46%	1.27%	1.10%
	Median	0.56%	0.66%	0.50%	0.43%	0.71%
	Std. Dev.	10.87%	12.32%	9.81%	9.57%	11.46%

The mean return in the lowest quartile of representativeness heuristic is significantly higher compared to the highest quartile. This is in line with the findings of Chen et al. (2007) that extrapolation of past returns is negatively related to return. Although not presented here, within the first quartile, the return first increases and then decreases afterwards. Hence it can be concluded that chasing positive return improves trade performance if the trend is short term. Chasing positive return in the longer term deteriorates wealth.

Robustness Checks

30 and 90 trading day positive return trends are used as alternative proxies for representativeness heuristic. Table 23 presents the descriptive statistics for these proxies.

Table 23. Descriptive Statistics for Representativeness Heuristic Alternative Proxies

30 Trading Day Positive Return Trend	N	Min	Max	Mean	Median	Std. Dev.
	243,644	0	1.00	0.467	0.466	0.05

90 Trading Day Positive Return Trend	N	Min	Max	Mean	Median	Std. Dev.
	243,644	0	1.00	0.469	0.468	0.04

Mean figures for 30 and 90 trading day positive return trends are very similar to those of 150 trading day positive return trend.

Table 5 shows that the correlation among 30, 90 and 150 trading day positive return trend is high and statistically significant. Table 24 shows regression results for the 30 and 90 trading day positive return trend.

Table 24. Regression Results for Representativeness Heuristic Using Alternative Proxies

	90 Day Trend	30 Day Trend
Constant		
Age	0.043*** (18.6)	0.028*** (12.1)
Male	-0.052*** (-25.6)	-0.051*** (-25.0)
Experience	-0.003 (-1.1)	0.006** (2.4)
Wealth_Low	-0.007*** (-3.3)	-0.004** (-2.0)
Wealth_High	0.023*** (10.8)	0.011*** (5.2)
Marmara	0.035*** (17.1)	0.028*** (13.6)
Southeast	-0.011*** (-5.3)	-0.012*** (-5.7)
Obs	243,644	243,644
R^2	0.008	0.006
Adjusted R^2	0.008	0.005

*** and ** indicate coefficient is significant at 1% and 5% respectively. t values in parentheses.

The dependent variable is 90 and 30 trading day positive return trend and independent variables are age, gender (in the form of male dummy), experience, wealth (in the form of dummy variables for low and high wealth categories) and geographical region of residence (in the form of dummy variables for Marmara and Southeast Anatolia regions). Wealth_Low is dummy for portfolio value less than 10,000 TL and

Wealth_High is dummy for portfolio value above 100,000 TL. The results confirm those of the 150 trading day positive return trend.

Results are further confirmed using different robustness checks. The findings are similar for sub samples (male only, female only, low / high age, low / high experience, and low / high wealth regressions). Findings are also robust for different regression models (using categorical vs. continuous explanatory variables). The findings are confirmed when stock return is used instead of market adjusted stock return. Furthermore, the results do not change when the expanded investor set (including high turnover investors) is used. However, the results are not presented here for the sake of brevity.

Status Quo Bias

Portfolio percentage change is the only proxy to measure status quo bias. Yet, several alternative analyses have been employed to check the robustness.

Portfolio Percentage Change

Portfolio percentage change is the daily change in the portfolio taking the change in the number of stocks compared to previous day into account.

Table 25 shows that the mean daily portfolio change of investors is 4% (median 2.17%).

Table 25. Descriptive Statistics for Portfolio Percentage Change

	N	Min	Max	Mean	Median	Std. Dev.
Portfolio Percentage Change	244,146	0	0.86	0.04	0.02	0.05

The histogram in Fig. 7 shows that 29% of the investors have a daily portfolio change of 1% or less.

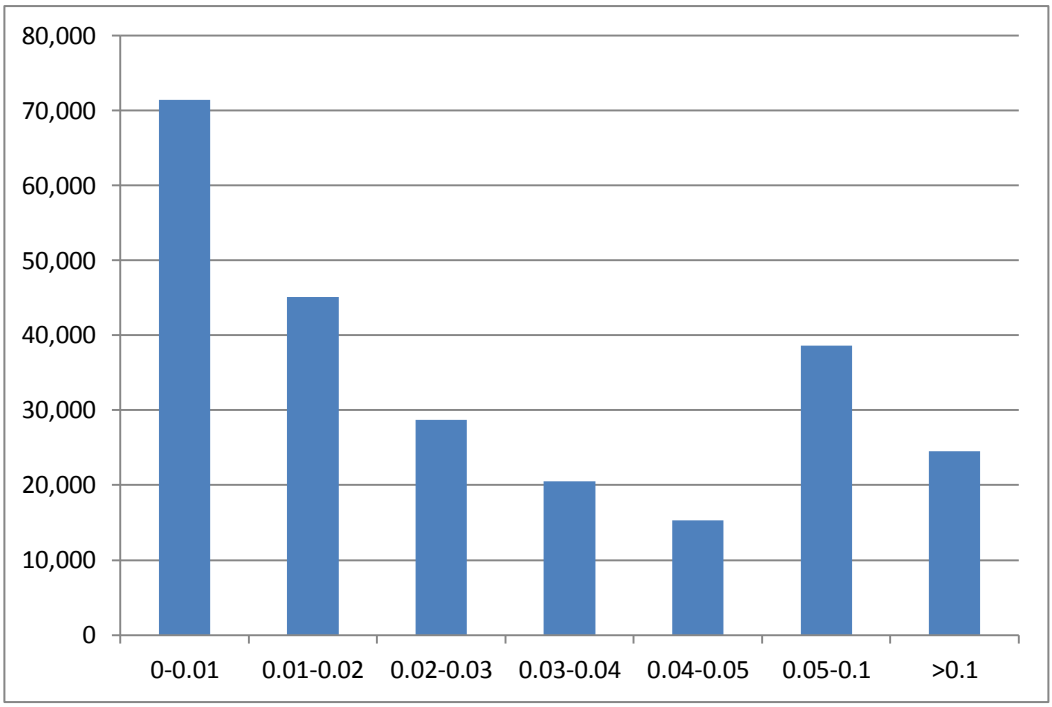

Fig. 7 Portfolio percentage change histogram

The annual turnover is 2.96 for the lowest daily portfolio change group, whereas it increases to 34.27 for the highest daily portfolio change group. Annual turnover and daily portfolio change is high (0.54) and statistically significant. These findings imply that a portion of investors exhibit status quo bias and investors on the opposite edge of overconfidence exhibit status quo bias. Table 26 shows the mean portfolio percentage change for each gender, age, wealth, experience and region category. Table 27 shows the regression results.

Table 26. Mean Portfolio Percentage Change for Each Demographic Breakdown

		Portfolio Percentage Change
	Total	0.040
Gender	Male	0.043
	Female	0.029
Experience	After 2008	0.058
	2006-2008	0.050
	2003-2005	0.039
	2000-2002	0.034
	Before 2000	0.029
Age	25<	0.051
	25-29	0.053
	30-34	0.050
	35-39	0.045
	40-44	0.040
	45-49	0.035
	50-54	0.031
	55-59	0.029
	60≥	0.024
Wealth	100-1,000	0.064
	1,000-5,000	0.058
	5,000-10,000	0.044
	10,000-20,000	0.040
	20,000-50,000	0.036
	50,000-100,000	0.032
	100,000-250,000	0.029
	250,000-500,000	0.027
	500,000-1M	0.025
	1M-5M	0.025
	5M+	0.024
Region	N/A	0.038
	Aegean	0.039
	Black Sea	0.040
	Central Anatolia	0.041
	East Anatolia	0.049
	Marmara	0.039
	Mediterranean	0.043
	Southeast Anatolia	0.051

Table 27. Regression Results for Portfolio Percentage Change

	Portfolio Percentage Change
Constant	
Age	-0.085*** (-37.6)
Male	0.091*** (46.0)
Experience	-0.109*** (-48.5)
Wealth_Low	0.089*** (42.1)
Wealth_High	-0.023*** (-10.8)
Marmara	-0.016*** (-7.9)
Southeast	0.014*** (7.0)
Obs	244,146
R^2	0.058
Adjusted R^2	0.058

*** indicates coefficient is significant at 1%. t values in parentheses.

The dependent variable is daily percentage change and independent variables are age, gender (in the form of male dummy), experience, wealth (in the form of dummy variables for low and high wealth categories) and geographical region of residence (in the form of dummy variables for Marmara and Southeast Anatolia regions). Wealth_Low is dummy for portfolio value less than 10,000 TL and Wealth_High is dummy for portfolio value above 100,000 TL. Since portfolio percentage change measures daily level of change in portfolio, higher values indicate lower status quo bias.

In line with expectations, demographic factors affect status quo bias opposite to that of overconfidence. Status quo bias increases with age. However, as Table 26 shows, age is nonlinearly related to status quo, decreasing up to the 25-29 age group, and

increasing afterwards. The nonlinear relationship is also confirmed by quadratic age term in the regression, which is not presented here for brevity. Male investors exhibit less status quo bias than female investors. Experience increases status quo bias. As an investor may gain experience in a shorter period of time with high-frequency trading, the account opening date does not necessarily imply experience. However, when an alternative definition of experience is used (the year when investors first reach 5,000 TL stock portfolio), the results do not change. Wealthy investors do not change their portfolio compositions as often as low wealth investors do. Investors in the Marmara region have a higher and investors in the Southeast Anatolia region have a lower status quo bias. The difference between these two regions is not related to gender, age, experience or wealth. The results imply that sophisticated investors exhibit more status quo bias.

Behavioral finance literature shows that trading is hazardous to wealth and suggests that investors should not trade frequently. Yet, there is no consensus on an optimum level of trading. Hence, too little trading can also lead to deterioration in wealth. However, the correlation between return and status quo bias is low but positive. Table 28 further presents a positive relation between return and portfolio percentage change.

Table 28. Mean Return for Portfolio Percentage Change

	Return	Total	1st Quartile Lowest 25%	2nd Quartile	3rd Quartile	4th Quartile Highest 25%
Portfolio Percentage Change	Mean	1.37%	2.83%	1.95%	1.00%	0.10%
	Median	0.56%	2.28%	1.69%	0.62%	-0.11%
	Std. Dev.	10.87%	18.22%	11.95%	6.57%	3.05%

The mean return in the lowest quartile of portfolio percentage change is significantly higher compared to the highest quartile. Moreover, as presented in Table 10, in line with the literature, men have a lower return than women. Although these results indicate that status quo is beneficial to wealth, like the disposition effect, further analysis is required to better understand the performance of stocks sold and held to better understand impact of status quo on wealth.

Robustness Checks

The regression results are confirmed using different robustness checks, yet not presented here for brevity. The findings are similar for sub samples (male only, female only, low / high age, low / high experience, and low / high wealth regressions). Findings are also robust for different regression models (using categorical vs. continuous explanatory variables). The results do not change when the expanded investor set (including high turnover investors) is used. The results are also confirmed when the percentage of active days (the number of days buy or sell transaction taking place divided by the number of days account is open in 2011) and the number of stocks subject to buy and sell for the investor within 2011 is taken into account as control variables in the regression.

Disposition Effect

In line with the literature, PGR / PLR is used as the primary proxy to measure disposition effect, accompanied by duration difference between gains and losses as well as several alternative analyses for robustness checks.

PGR / PLR

PGR/PLR cannot be calculated for 81,686 investors. This is because either PGR cannot be calculated (due to the fact that no realized and paper gain exists) or PLR is zero (due

to the fact that no realized loss exists) or PLR cannot be calculated (due to the fact that no realized and paper loss exists). Hence, the analysis is based on the remaining 162,460 investors. Disposition effect is calculated based on the paired sell and buy transactions. Of these, all sell transactions are matched with a purchase transaction (100% match ratio) for 20% of the investors. For 61% of the investors, the match ratio is 90% or above and for 95% of the investors, the match ratio is 50% or above.

Table 29 shows that the mean PGR/PLR is 3.77 and the median PGR / PLR is 1.95.

Table 29. Descriptive Statistics for PGR / PLR

	N	Min	Max	Mean	Median	Std. Dev.
PGR / PLR	162,460	0	2,524.02	3.77	1.95	11.25

Disposition effect decreases to 2.55 for high turnover investors. The histogram in Fig. 8 shows that 17% of the investors have PGR/PLR lower than or equal to one, implying these investors do not exhibit disposition effect.

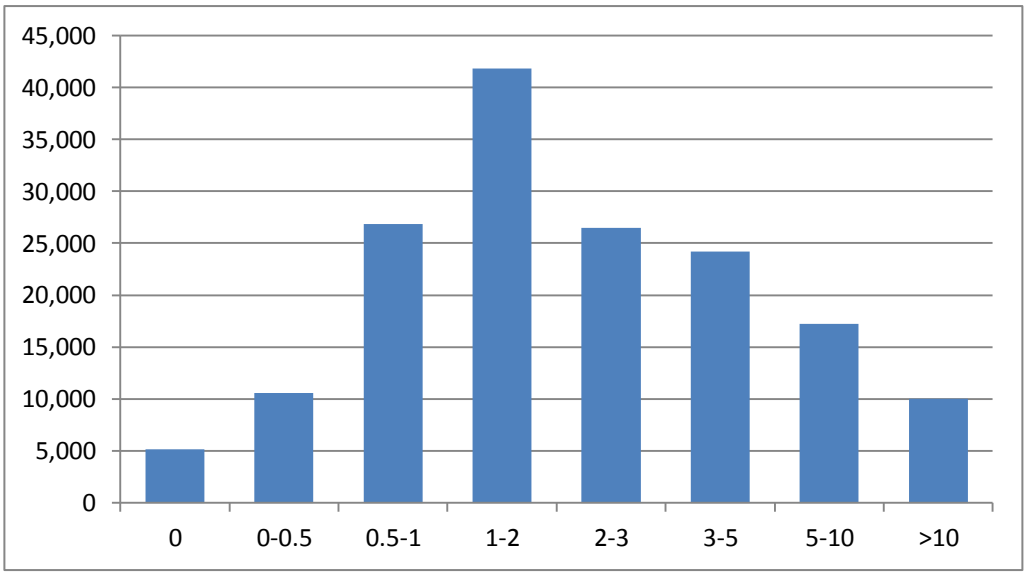

Fig. 8 PGR / PLR histogram

The mean PGR/PLR is 3.79 among investors with match ratio above 50% and 3.58 among investors with match ratio above 90%. All these figures show that individual Turkish investors are prone to disposition effect. Besides this, the disposition effect for individual Turkish investors is high compared to international benchmarks. Odean (1998b) finds that the mean PGR - PLR is 0.05 for US individuals based on data from a brokerage house. Dhar and Zhu (2006) find that PGR - PLR is 0.21 for US individuals based on a brokerage house data. Chen et al (2007) compute PGR – PLR for Chinese individual investors to be 0.21. In this study, mean PGR – PLR is 0.24 and median PGR-PLR is computed as 0.28. The results are similar, both in individualistic countries such as the USA and collectivist countries such as China and Turkey. Yet the figures imply that individual Turkish investors have a higher tendency to exhibit disposition effect.

Table 30 shows the mean PGR / PLR for each gender, age, wealth, experience and region category. Table 31 shows the regression results.

Table 30. Mean PGR / PLR for Each Demographic Breakdown

		PGR / PLR
	Total	3.77
Gender	Male	3.68
	Female	4.32
Experience	After 2008	3.14
	2006-2008	3.37
	2003-2005	3.88
	2000-2002	3.88
	Before 2000	4.33
Age	25<	3.50
	25-29	3.18
	30-34	3.29
	35-39	3.57
	40-44	3.55
	45-49	4.05
	50-54	4.26
	55-59	4.62
	60≥	5.09
Wealth	100-1,000	1.98
	1,000-5,000	2.40
	5,000-10,000	2.89
	10,000-20,000	3.42
	20,000-50,000	3.85
	50,000-100,000	4.73
	100,000-250,000	5.31
	250,000-500,000	6.65
	500,000-1M	7.43
	1M-5M	8.30
	5M+	9.76
Region	N/A	4.54
	Aegean	3.91
	Black Sea	3.40
	Central Anatolia	3.90
	East Anatolia	3.04
	Marmara	3.82
	Mediterranean	3.71
	Southeast Anatolia	3.44

Table 31. Regression Results for PGR / PLR

	PGR/PLR
Constant	
Age	0.017*** (5.8)
Male	-0.017*** (-6.8)
Experience	0.000 (0.0)
Wealth_Low	-0.048*** (-18.0)
Wealth_High	0.064*** (24.3)
Marmara	-0.003 (-1.4)
Southeast	-0.001 (-0.2)
Obs	162,460
R^2	0.010
Adjusted R^2	0.010

*** indicates coefficient is significant at 1%. t values in parentheses.

The dependent variable is PGR/PLR and independent variables are age, gender (in the form of male dummy), experience, wealth (in the form of dummy variables for low and high wealth categories) and geographical region of residence (in the form of dummy variables for Marmara and Southeast Anatolia regions). Wealth_Low is dummy for portfolio value less than 10,000 TL and Wealth_High is dummy for portfolio value above 100,000 TL.

Results indicate that demographic factors affect disposition effect differently than they do overconfidence. Disposition effect increases with age. However, as Table 30 shows the mean PGR / PLR for each gender, age, wealth, experience and region category. Table 31 shows the regression results.

Table 30 shows age is nonlinearly related to disposition effect, decreasing up to the 25-29 age group, and increasing afterwards. The nonlinear relationship is also confirmed by quadratic age term in the regression, which is not presented here for brevity. The disposition effect is lower for male investors. The mean PGR is 0.506 for male and 0.549 for female investors, the difference is statistically significant at 1%. The mean PLR is 0.278 for male and 0.271 for female investors, with the difference still statistically significant at 1% (figures not presented for brevity). The figures show that women realize gains more than men, whereas difference in loss realization is less pronounced. This may be due to the fact that women are less overconfident than men, so when they find the opportunity, they realize gains without waiting for further price increases. Experience does not have a statistically significant impact on disposition effect. However, when an alternative definition of experience is used (the year when investors first reach 5,000 TL stock portfolio), experience decreases the disposition effect. Wealth increases the disposition effect. The mean PGR is 0.459 for wealthy investors (wealth higher than 100,000 TL) and 0.545 for low wealth investors (wealth lower than 10,000 TL). The mean PLR is 0.195 for wealthy investors and 0.335 for low wealth investors. The difference in PLR is more pronounced compared to PGR. Hence, it can be inferred that low wealth investors realize losses more than wealthy investors. One possible explanation is the liquidity needs of low wealth investors as wealthy investors have better access to liquidity. Hence, low wealth investors may have to realize losses to a higher degree. Thus, wealth per se may not increase the disposition effect. Being in the Marmara or Southeast Anatolia region does not have a statistically significant impact on disposition effect. This is due to the fact that investors in the Aegean region have highest PGR/PLR ratio followed by the Central Anatolia and the

Marmara regions and investors in the East Anatolia region have lowest PGR/PLR ratio followed by the Black Sea and the Southeast Anatolia regions. Wealth and region results are not supportive enough to argue that sophisticated investors are more prone to disposition effect.

The correlation between return and disposition effect is positive and significant (correlation 0.132), as implied by the definition of the measurement method. Besides this, the correlation between turnover and disposition effect does not change with including high turnover investors. These results are similar to the findings of Chen et al (2007). Positive relation between return and disposition effect is further presented in Table 32.

Table 32. Mean Return for PGR / PLR

	Return	Total	1st Quartile Lowest 25%	2nd Quartile	3rd Quartile	4th Quartile Highest 25%
PGR / PLR	Mean	1.37%	-1.44%	-0.12%	0.45%	3.04%
	Median	0.56%	-0.84%	-0.37%	0.05%	1.81%
	Std. Dev.	10.87%	8.68%	5.67%	6.11%	7.76%

The mean return in the lowest quartile of PGR / PLR is significantly lower compared to the highest quartile.

Robustness Checks

Although not presented here for brevity, the robustness checks confirm the findings.

Similar to the calculation of Shefrin and Statman (1985), the difference between the average holding period for gains and losses is significant (31 trading days for gains vs. 17 trading days for losses), further confirming the results.

The findings are similar for sub samples (male only, female only, low / high age, low / high experience, and low / high wealth regressions). Results are also robust for different regression models (using categorical vs. continuous explanatory variables). The results do not change when the expanded investor set (including high turnover investors) is used. The results are also confirmed when investor set is limited to match ratio above 50% or 90%. Moreover, the main results are confirmed when PGR - PLR is used instead of PGR / PLR.

Relationship Among Biases

Table 33 shows the correlations among biases.

Table 33. Correlation among Biases

	Turnover	Previous Ownership Ratio	150 Trading Day Pos. Return Trend	Portfolio Perc. Change
Previous Ownership Ratio	0.310***			
150 Trading Day Pos. Return Trend	-0.031***	-0.064***		
Portfolio Perc. Change	0.540***	0.330***	-0.057***	
PGR/PLR	-0.052***	0.043***	-0.024***	-0.047***

*** indicates significant at 1%

The correlation between overconfidence and familiarity bias (in other words turnover and previous ownership ratio) is 0.310 and statistically significant. However, overconfidence is negatively correlated with the representativeness heuristic, status quo bias and disposition effect. Our findings are in line with those of Chen et al. (2007), who

show that in China overconfident investors are less prone to disposition effect and the representativeness heuristic.

Moreover, familiarity bias is negatively correlated with the representativeness heuristic and status quo bias, whereas it is positively related to disposition effect. The representativeness heuristic is positively correlated with status quo bias but negatively correlated with disposition effect, while Chen et al (2007) report a positive correlation among Chinese investors. Finally, status quo is positively correlated with disposition effect. In results that are omitted for brevity, similar findings are reported for the expanded investor set including high turnover investors.

The effect of each bias on return is also analyzed in a multivariate regression model. Table 34 presents the regression results. Although relationship between return and biases are well detailed in previous findings, this analysis intends to confirm the findings taking all biases as well as demographics into account simultaneously.

Table 34. Regression Results for Return

	Return										
Constant											
Overconfidence *(Tunover)*	-0.066*** (-31.4)					-0.059*** (-28.1)					-0.041*** (-14.0)
Familiarity *(Previous Ownership)*		0.008*** (3.8)					-0.001 (-0.7)				0.075*** (28.1)
Representativeness *(150 Day Trend)*			-0.039*** (-18.6)					-0.044*** (-21.2)			-0.030*** (-12.3)
Status Quo *(Portfolio % Change)*				-0.072*** (-34.2)					-0.054*** (-25.3)		-0.023*** (-7.3)
Disposition Effect *(PGR/PLR)*					0.132*** (53.6)					0.124*** (50.3)	0.119*** (48.5)
Age						0.018*** (7.5)	0.021*** (8.5)	0.021*** (8.8)	0.017*** (7.0)	0.011*** (3.8)	0.010*** (3.6)
Gender						-0.033*** (-15.7)	-0.037*** (-17.6)	-0.039*** (-18.4)	-0.033*** (-15.5)	-0.024*** (-9.8)	-0.026*** (-10.3)
Experience						0.012*** (5.0)	0.010*** (4.2)	0.009*** (3.9)	0.004* (1.7)	0.009*** (3.2)	0.003 (1.1)
Wealth_Low						-0.063*** (-28.1)	-0.065*** (-28.6)	-0.065*** (-28.9)	-0.060*** (-26.5)	-0.065*** (-24.7)	-0.051*** (-19.1)
Wealth_High						0.028*** (12.4)	0.030*** (13.2)	0.032*** (14.2)	0.028*** (12.6)	0.028*** (10.6)	0.020*** (7.7)
Marmara						0.003 (1.4)	0.004* (1.8)	0.004** (2.0)	0.003 (1.4)	0.005** (2.0)	0.006** (2.5)
Southeast						-0.006*** (-2.7)	-0.006*** (-3.0)	-0.008*** (-3.3)	-0.006*** (-2.7)	-0.005* (-1.9)	-0.005** (-2.1)
Obs	226,173	226,173	226,173	226,173	162,460	226,173	226,173	226,173	226,173	162,460	162,460
R^2	0.004	0	0.002	0.005	0.017	0.013	0.01	0.012	0.013	0.025	0.032
Adjusted R^2	0.004	0	0.002	0.005	0.017	0.013	0.01	0.012	0.013	0.025	0.032

***, **, and * indicate significant at 1%, 5%, and 10% respectively. t values in parentheses.

Previous findings in the literature show that investors trading aggressively underperform. The negative effect of overconfidence on return is confirmed. However, investors who tend to buy familiar stocks have better returns. One possible explanation is the information effect as the investors are more likely have more information for stocks that they frequently trade. Similar to overconfidence, representativeness heuristic relates to underperformance. Confirming the previous findings, investors chasing positive returns end up with lower returns. Status quo bias is on the opposite edge of overconfidence. Thus, contrary to overconfidence, investors who do not trade frequently have higher returns. As investors exhibiting disposition effect tend to realize gains more often, disposition effect increases return.

CHAPTER 5

CONCLUSION

Empirical studies in the behavioral finance literature show that individuals do not behave rationally. The behavioral biases govern investor decisions and affect financial markets. However, these studies are either limited to the subsamples of the overall investor groups studied, or look at one bias at a time, and mainly focus on individualistic countries such as the U.S. and Europe. This thesis focuses on Turkey, which is an emerging market with a collectivist culture. In this thesis, it is analyzed how prevalent overconfidence, familiarity bias, representativeness heuristic, status quo bias and disposition effect are among individual Turkish stock investors, what factors affect these biases, and how these biases relate to each other and return performance using transaction and demographic data.

Using Turkish nationwide data for buy and sell transactions of the individual investors for the year 2011, several interesting findings are reported. First, overconfidence is highly common among investors. Individual Turkish investors exhibit more overconfident behavior compared to that observed in the behavioral finance literature. In line with literature, male investors exhibit more overconfidence than female investors. Age and wealth decrease overconfidence. Investors in more developed regions are less overconfident than those in the less developed regions. Wealth and region results imply that sophisticated investors are less prone to overconfidence. Overconfidence is hazardous to wealth, as the mean return decreases with increasing turnover. Moreover, in line with literature, men have lower return than women, as men

are more overconfident. It is also found that results for the status quo bias are consistent with overconfidence results and individuals exhibiting status quo bias are in the opposite edge of overconfidence scale.

Familiarity bias is also common among individual Turkish stock investors. Male investors are more prone to familiarity bias compared to female investors. Age and wealth decrease familiarity bias. Investors in the more developed regions are less prone to familiarity bias than those in the less developed regions. Wealth and region results imply that sophisticated investors are less prone to familiarity bias.

Individual Turkish stock investors do not seem to be positive return chasers. Demographic factors affect representativeness heuristic in just the opposite way they do the overconfidence and familiarity bias. Investors chasing positive past returns yield lower returns. However, mean recent past positive return ratios of stocks purchased are not economically different across different investor groups in terms of gender, age, wealth, experience and region of residence.

Finally, it is found that disposition effect is common among individual Turkish stock investors. Disposition effect increases with age, male investors exhibit disposition effect less than female investors, wealth increases disposition effect, and experience and region do not have a statistically significant impact on the disposition effect. As disposition effect definition implies, investors exhibiting the disposition effect have higher returns and they realize gains more often.

This thesis also focuses on the interactions among the biases and it is found that overconfidence is positively correlated with familiarity bias. In line with expectations, overconfidence is negatively correlated with status quo bias. Furthermore, familiarity

bias is negatively correlated with status quo bias. Correlation among other biases is also significant yet less pronounced.

The findings in this thesis are robust to the use of different subsamples, regression models, proxies and expansion of the investor set to include high turnover investors. The high turnover investors possibly have their wealth managed by professional money managers and / or they act like day traders and scalpers.

Overall, the results of this thesis are line with the findings for China and Taiwan to show that individual investors in an emerging economy with collectivist characteristics are prone to behavioral biases as well, generally to a higher extent, compared to their counterparts in the developed and mostly individualistic economies. Consequently, it is reasonable to expect similar results in the other emerging markets, most of which are observed to be collectivist countries as well.

Additionally, behavioral biases are affected by demographic factors and have impact on the trade performances of the investors. Apart from the disposition effect, which has the highest impact on returns due to the construction of the measure, the most pronounced effect is that of the overconfidence and familiarity bias. Moreover, in line with the literature, behavioral biases are correlated among each other to some extent, but the most evident relationship is between overconfidence and familiarity bias.

It would be worth investigating the familiarity bias, which is not studied as much as the overconfidence and disposition effect in the literature. Besides this, it would also worth analyzing the evolution of behavioral biases by looking at the change of level of each bias in the years following 2011.

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