

COMPARISON OF INVESTOR BEHAVIOR
BETWEEN REAL AND SIMULATED TRADING ENVIRONMENTS

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DECLARATION OF ORIGINALITY

I, Doğaç Şenol, certify that

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- this is a true copy of the thesis approved by my advisor and thesis committee at Boğaziçi University, including final revisions required by them.

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ABSTRACT

Comparison of Investor Behavior Between Real and Simulated Trading Environments

Investment behavior between real and simulated trading environments are compared and whether gamification can help mitigate behavioral biases of investors is investigated by conducting a unique stock market experiment that is free from observer-expectancy and subject-expectancy effects. Utilizing the trading data of investors who simultaneously have active portfolios in an investment firm and stock market simulation game, it is shown that investors have different biases in real versus simulated settings. Participating in a stock market game is found to be affecting all biases differently, with different degrees of participation to the game. While overconfidence bias and disposition effect can be mitigated and decrease with more active participation in the game, familiarity and status quo biases increase. It is also shown that young, inexperienced investors with average-sized portfolios and men are more likely to participate. These findings will especially be of interest to researchers, financial institutions and policy makers that plan to conduct similar experiments and design services promoting better financial decision-making and investment behavior.

ÖZET

Gerçek ve Simüle Edilmiş Borsa Alım-Satım Ortamları Arasındaki Yatırımcı Davranışlarının Karşılaştırılması

Gerçek ve simüle edilmiş borsa alım-satım ortamları arasındaki yatırımcı davranışları karşılaştırılmış ve oyunlaştırmanın yatırımcıların davranışsal önyargılarını azaltmaya yardımcı olup olamayacağı, gözlemci-beklenti ve denek-beklenti etkilerinden arındırılmış bir borsa deneyi gerçekleştirilerek araştırılmıştır. Bir yatırım firmasında ve borsa simülasyon oyununda eş zamanlı olarak aktif portföyleri olan yatırımcıların alım satım verilerini kullanarak, yatırımcıların gerçek ve simüle ortamlarda farklı önyargılara sahip olduğu gösterilmiştir. Bir borsa oyununa katılmanın, katılım derecesine göre değişmekle birlikte, yatırımcı önyargılarını farklı şekilde etkilediği gözlemlenmiştir. Aşırı güven (overconfidence) önyargısı ve yakınlık etkisi (disposition effect) oyuna aktif katıldıkça azalırken, aşinalık (familiarity) ve statüko (status quo) önyargıları artmaktadır. Ayrıca, genç, deneyimsiz ve ortalama büyüklükte portföylere sahip yatırımcıların ve erkeklerin oyuna katılma olasılıklarının daha yüksek olduğu görülmüştür. Bu bulgular, özellikle benzer deneyler yapmayı ve daha iyi finansal karar verme ve yatırım davranışını teşvik eden hizmetler tasarlamayı planlayan araştırmacılar, finans kurumları ve devlet kurumları için ilgi çekici olacaktır.

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CHAPTER 1

INTRODUCTION

Gamification is gaining popularity as one of the methods to embrace, motivate and educate people to improve financial behavior (Bayuk & Altobello, 2019). There is growing evidence in the literature that gamification works (Hamari & Koivisto, 2015a). While FinTech companies use gamification as a means of improving financial behavior and thereof access to financial services (Bitrián, Buil, & Catalán, 2021; Pal, Indapurkar, & Gupta, 2021; Sironi, 2016), policy makers explore gamification to achieve sustainable development goals (Hassan & Hamari, 2020). Financial literacy, a set of knowledge and skills necessary to make informed financial decisions, is gaining more significance with policy makers' focus to improve the welfare of the society through financial education (Corsini & Giannelli, 2021; Koh, 2016; Lusardi & Mitchell, 2014; OECD, 2020; Taylor & Wagland, 2011).

Literature on financial literacy focuses on measuring, emphasizing the importance of and improving financial knowledge, however it is not enough unless it is also manifested in financial behavior (Goyal & Kumar, 2021). While financial knowledge and skills have been an important pillar of financial well-being, financial behavior and its association with behavioral biases remains rather a niche research area (Riitsalu & Murakas, 2019). Yet there is recent evidence of a relationship between financial literacy of investors and some of the behavioral biases they may bear (Baker, Kumar, Goyal, & Gaur, 2019; Zahera & Bansal, 2018). While determinants of behavioral biases are well documented (de Bondt, Muradoglu, Shefrin, & Staikouras, 2008; Kumar & Goyal, 2015), mainstream research focuses

on various methods of measuring them, rather than mitigating them (D. F. Costa, de Melo Carvalho, de Melo Moreira, & do Prado, 2017). This research proposes to fill this gap by using a unique dataset of 693 distinct investors' real and simulated investment behaviors, which enables testing whether behavioral biases can be mitigated via gamification.

Existing experimental studies in investments that examine the impact of gamification on financial behavior are predominantly stock market simulation games, where students participate as part of an economics class or other means of financial education. Using convenient subjects like this in experiments is prone to some limitations (Bhattacharya, Gill, & Stanley, 2016; Kaiser & Menkhoff, 2020; Smith & Gibbs, 2020; Stewart, Houghton, & Rogers, 2012). Most importantly, presence of subject-expectancy effect and observer-expectancy effect is a risk on the validity of the experiment. The subject-expectancy effect occurs when participants in an experiment suspect or are aware that they are participating in a study and behave according to it, threatening real world validity of the experiment (Parsons, McCormac, Pattinson, Butavicius, & Jerram, 2013). Observer-expectancy effect, also called experimenter-expectancy effect, refers to the bias the experimenter may induce when constructing or evaluating the experiment. It is not unknown that educational experiments are prone to this bias (Kocakaya, 2011).

This research differentiates from these studies and presents a unique experimental setting. The dataset has 17598 observations of 693 distinct investors, who simultaneously have accounts in an established investment firm and have also participated in a stock market simulation game. This setting allows to observe and compare the investment choices of investors in an observer-expectancy effect-free environment. More importantly it enables investigating whether the introduction of

gamification improves financial behavior by reducing the biases of investors over time. Accordingly, first, whether the level of behavioral biases of investors in stock market simulation games is different from real trading environments is tested, providing valuable insight to researchers who would like to carry out similar experiments. Secondly, how these behavioral biases in real trading environments are affected after participating in a stock market simulation game is determined, evaluating the efficacy of gamification in financial behavior and decision-making. Lastly, the demographics of investors who voluntarily enrolled in the stock market game are reported, providing an important starting point to researchers, policy makers, financial services institutions and their marketing departments in determining the appropriate target audiences for similar environments or experiments.

This study contributes to the literature by showing how gamification may help alleviate behavioral biases and the demographics that play a role in the decision to participate in one. First, it is found that for every case measured, behavioral biases of investors are significantly different in real versus simulated environments. This difference persists at different levels of investors' activeness in the simulation game. Secondly, it is found that participating in a stock market simulation game affects all biases but significantly decreases some in the real trading environment. For overconfidence bias and disposition effect, a significant decrease is observed. This effect becomes more pronounced as the investors' activeness in the simulation increases. However, for the familiarity bias and status quo bias, a significant increase is found. Lastly, gender, age, region, trading experience and wealth factors are found to be important in motivating people to actively join a stock market simulation game. These findings will especially be of interest to researchers, financial institutions and

policy makers that plan to conduct similar experiments by providing insight on (i) the dynamics of behavioral biases in stock market simulation games in contrast to real trading environments, (ii) the impact of gamification on investors' behavioral biases, and, (iii) the design and delivery of financial services to improve financial behavior and thereby financial inclusion.

The rest of this thesis is organized as follows: Next, Chapter 2 is a literature review and in Chapter 3 each of the respective hypotheses is presented. Chapter 4 explains the unique dataset, experiment and the methodology followed in analyzing it, including the variables and their operationalization. Chapter 5 presents the results and Chapter 6 the discussion of the results and their implications. Chapter 7 concludes this thesis with limitations and future recommendations.

CHAPTER 2

LITERATURE REVIEW

This chapter is a comprehensive review of behavioral finance, with a focus on behavioral biases of investors and gamification, especially stock market simulation games.

2.1 Behavioral finance

The decisions investors make have long been thought of as a merit of rational behavior. Traditionally, anything investors do has always been modeled to be based on rational information they possess (Simon, 1955). Revolutionary research from Tversky and Kahneman (1974) and Kahneman and Tversky (1979) held a new spotlight and completely different point of view to the factors affecting how investors behave. It is shown that in addition to rational thinking, lots of other factors from the field of psychology like moods, emotions and behavioral biases have a huge impact on their decision-making process. Hence, behavioral finance as the study of the effects of non-rational behavior on investors is born. As a relatively new field between finance and psychology, behavioral finance studies investor decision-making processes to understand phenomena previously defined as “anomalies” since they could not be explained with neoclassical finance (de Bondt et al., 2008). Nigam, Srivastava and Banwet (2018) study behavioral finance under three main dimensions: Information, demographics and behavioral biases.

2.1.1 Information

Information is a key factor in every decision-making process. A couple of important aspects like quality, reliability and accessibility of the information about the company directly impact the decision of investing. This information may arrive from official or unofficial resources like media, research reports and analyst recommendations (Nigam et al., 2018). This research leaves the information aspect of behavioral finance out of scope, as there is no information on which information the investors had access.

2.1.2 Demographics

Demographics, including socio-economic and socio-cultural factors like age, gender, wealth, education, financial literacy and location have been shown to affect the decision-making process of investors. Vissing-Jorgensen (2003) suggests that investor sophistication, proxied by wealth and investor experience, has a negative correlation with irrational behavior. Ackert, Church and Tkac (2010) conclude that training, knowledge and experience have a significant effect on financial decision-making. Abreu and Mendes (2010) emphasize that investors living in financially developed metropolitan areas diversify their portfolios better. They also state that male investors diversify their portfolios more, suggesting higher financial literacy and lower overconfidence compared to female investors. Lin (2011) demonstrates that male and female investors differ in their behavioral biases they possess, namely disposition effect, herding and overconfidence. Roche, Tompaidis and Yang (2013) report portfolio diversification is influenced by age and financial wealth. Cronqvist and Siegel (2014) report that genetic differences explain up to 45% of the variation across investors. Chavali and Mohanraj (2016) report a link between investors'

demographic characteristics and their investment behavior. According to the findings, gender is an important variable influencing individual investors' investment decisions. Tekçe, Yilmaz and Bildik (2016) found that different levels of behavioral biases exist among Turkish investors with respect to demographics like gender, age, wealth and location. Shusha and Touny (2016) investigate herding behavior in Egyptian Stock Exchange and find that certain demographics moderate herding behavior of investors. Baker et al. (2019) study how demographics and financial literacy are related to behavioral biases and report that age, occupation and investment experience are the most important demographic variables affecting behavioral biases of investors. They also find that male investors are more overconfident than female investors and financial literacy is negatively related to disposition effect and herding bias, positively related to mental accounting bias but interestingly not related to overconfidence bias or emotional biases. Li (2020) reports that a lower level of financial literacy leads to more irrational behavior among investors. Chhatwani and Mishra (2021) study the relationship between financial literacy and financial fragility and report that financial literacy reduced fragility by 9.1%, and even more for investors with more wealth. They also show that interaction with race is not a significant factor. Hsu, Chen, Huang and Lin (2021) investigate the effect of gender differences on investor behavioral biases and reveal that among average investors, men are more overconfident than women but for investors with a high level of financial literacy, the level of behavioral biases are similar, suggesting that financial literacy mitigates gender differences in terms of financial behavior. Goyal and Kumar (2021) do a systematic literature review and conclude that there are still many questions open, especially about the factors that can affect the relationship between financial literacy, financial knowledge and financial behavior.

2.1.3 Behavioral biases

Behavioral biases are cognitive and psychological aspects that drive deviation from rationality in judgement. They are labeled as one of the main factors in explaining anomalies in the decision-making processes of investors (Baker et al., 2019).

Investment decisions cannot be described correctly without understanding the various behavioral biases in the decision-making mechanism as people are prone to many different biases when they invest (Sahi, Arora, & Dhameja, 2013). Some, but not all of the common behavioral biases are overconfidence, disposition effect, familiarity bias, status quo bias, anchoring, representativeness, availability, herding and mental accounting. This research focuses on the first four of these biases.

Behavioral finance literature has an increasing interest in behavioral biases. Shefrin and Statman (1985) study the habit of investors to sell winner stock early and hold onto loser stocks and defined this tendency as disposition effect. Heath and Tversky (1991) state that overconfident investors are more likely to underdiversify their portfolios and concentrate on stocks that they are more familiar with. Josephs, Larrick, Steele and Nisbett (1992) argue that high self-esteem individuals make decisions to minimize potential regret, taking less risks. Kahneman and Riepe (1998) state that people who do not constantly get involved with the same problems rely on probabilistic estimates and try to learn from the outcomes of their decisions, implying overconfidence. Thus, it can be said that experienced investors who trade every day are expected to have lesser overconfidence than individual investors do. Benos (1998) argues that overconfident investors think that they are smarter than the average and trade more aggressively when, in fact, most lack critical pieces of information and they try to forecast it. They also raise the question of the persistence of overconfidence. Daniel, Hirshleifer and Subrahmanyam (1998) state that due to

self-attribution, investors who become wealthier by successful investments may become more overconfident and as a result trade more aggressively. They also theorize that the effects of overconfidence are more intense in riskier securities. Odean (1998a) defines a framework to measure disposition effect using proxy variables derived from trading data. Odean (1998b, 1999) proposes that investors trade too much because of their overconfidence. Barber and Odean (1999) test for overconfidence and disposition effect and report that investors trade too much and tend to sell winner stocks early and hold onto losing stocks. Barber and Odean (2000) imply that in the overconfidence model, investors who trade more are expected to have lower expected utility, thus unsatisfactory outcomes. Barber and Odean (2001) state that people are overconfident in their abilities by nature and apply this body of knowledge to come to the conclusion that high levels of trading in stock markets are due to overconfidence. They analyzed a large brokerage house data and found that men trade more than women do because men are more overconfident than women in most areas, referencing vast literature in psychology. They add that some individuals, mostly men, to a lesser extent also women, may be trading for entertainment, resembling the act of gambling. Gervais and Odean (2001) support the view that investors are on average overconfident and investor size is a good proxy for overconfidence. They assert that overconfident investors do not possess greater profits, but investors who gain greater profits become more overconfident over time. They conclude that while time and experience result in reduction of overconfidence, there are enough new investors coming into the market to keep the average investor overconfident. Shapira and Venezia (2001) analyze investment patterns of Israeli investors and show that both professional and individual investors exhibit disposition effect. They also report that disposition effect is stronger with individual investors.

Genesove and Mayer (2001) show that this tendency also exists in the housing market and property owners are reluctant to realize losses. Grinblatt and Keloharju (2001) study Finnish market over a two-year period and conclude that investors are prone to disposition effect, thus reluctant to realize their losses. Daniel, Hirshleifer and Teoh (2002) also state that investors are more prone to realize their gains rather than their losses and mention the psychological effects that help explain this behavior. Vissing-Jorgensen (2003) reviews the literature on whether investor irrationality disappears with wealth and reports that many behavioral biases weaken with investor wealth. Brown, Chappel, da Silva Rosa and Walter (2005) find that disposition effect decreases over time and becomes undetectable after around 200 trading days. Massa & Simonov (2005) examine investor reactions to the definition of gains and losses and show that risk-taking in financial markets is affected by gains and losses in their overall wealth. Feng and Seasholes (2005) state that investors carry behavioral biases and neither investor sophistication nor trading experience alone eliminate behavioral biases. Campbell (2006) studies household finance and concludes that many households are overconfident and own few stocks, they tend to invest locally and have home bias and trade too much. Chuang and Lee (2006) study overconfident investors and conclude that they overestimate their abilities, underestimate risk and trade more in riskier securities. Hedesström, Svedsäter and Gärling (2006) argue that even when inexperienced investors diversify their portfolios to reduce risk, they are mostly unaware that some stocks they hold are from the same category, having covariation among them. This implies that diversification is important and recommended, but there should be minimal covariation between the invested securities. Kempf and Ruenzi (2006) report that investors hold status quo bias, but it depends on the number of available alternatives.

Dhar and Zhu (2006) investigate disposition effect and report that wealthier investors exhibit a lower disposition effect. They also state that frequent trading reduces it. Statman, Thorley and Vorkink (2006) observe long-term US stock trading activity and find that overconfidence and disposition effect are mostly seen in small-cap stocks where most of the shares are held by individual investors. Chuang and Lee (2006) provide evidence of overconfidence in financial markets and market gains make overconfident investors trade more aggressively. Barber, Lee, Liu and Odean (2007) analyze trading activity on the Taiwan Stock Exchange and report a strong reluctance to sell losing stocks, namely disposition effect. Glaser and Weber (2007) report that investors who are overconfident and who think they are above average in terms of investment skills trade more. Chen, Kim, Nofsinger and Rui (2007) categorize Chinese investors by experience using proxy measures and conclude that there is no significant difference between experienced and inexperienced investors in terms of behavioral biases. They used five specific measures, namely investing experience, age, trading frequency, personal wealth and residence location and conclude that none of these make investors exempt from behavioral biases. Ekholm and Pasternack (2008) state that it would be feasible to assume that, as investor wealth is a good proxy for overconfidence, managers of larger investment portfolios would be more experienced and less overconfident than smaller investors. They conclude that larger investors react more rationally to news. Goetzmann and Kumar (2008) imply that high portfolio turnover and under-diversification go side-by-side as a measure of overconfidence. Barber, Odean and Zhu (2009) analyze trading records at a large retail broker and document that behavioral biases lead investors to buy high-volume or recently well-performed stocks and hold onto losing stocks. Barber, Lee, Liu and Odean (2009) mention that individual investors are advised to avoid

trading too much and encouraged to buy and hold a diversified investment portfolio. They analyze four years of Taiwan stock market data and come to the conclusion that most losses are caused by aggressive orders, hinting overconfidence. They end by stating that most individuals have little or no financial literacy, hold underdiversified portfolios and give uninformed trading decisions. Glaser and Weber (2009) discuss that as portfolio turnover increases, investors reduce the number of stocks in their portfolio, leading to under-diversification. They apply this finding and use portfolio diversification as a proxy for overconfidence. Grinblatt and Keloharju (2009) study data from Finland and report that overconfident and sensation-seeking investors trade more frequently. Graham, Harvey, & Huang (2009) find that overconfident investors trade more often. They also report that educated, male investors with larger portfolios are more overconfident than female investors, investors with smaller portfolios or less education. Seru, Shumway and Stoffman (2010) state that there are two ways of investor self-learning; some investors persist and become better at trading over time by gradually lowering their behavioral biases and others stop early when they realize that their abilities are low. Deaves, Lüders and Schröder (2010) define overconfidence as the difference between certainty and knowledge. They also conclude that experience in the markets leads to overconfidence through reduced knowledge. They also report that failed investors have reduced overconfidence, in contrast to successful investors being more overconfident. Kimball and Shumway (2010) study home bias and report that as investor sophistication increases, exposure to home bias decreases. Abreu and Mendes (2010) suggest that more educated investors with high financial literacy have more diversified portfolios, thus exposed to less overconfidence. Talpsepp (2011) analyzes the Estonian stock market and finds that overall, investors possess disposition effect. They also report that foreign

investors, on the contrary, exhibit a "reverse disposition effect". Bailey, Kumar and Ng (2011) study behavioral biases of mutual fund investors and report that while investors with higher incomes and better education tend to hold mutual funds, investors with strong behavioral biases tend to trade individual stocks. (Grinblatt, Keloharju and Linnainmaa (2011) show that better investment behaviors like holding mutual funds, more diversified portfolios and experiencing lower risk, are positively related to IQ. Lin (2011) studies the Taiwanese stock market and finds that irrational behavior is present in various investment decision-making stages. Hoffmann, Shefrin and Pennings (2012) empirically identify investor segments and compare their investment styles. They conclude that investors who are strong believers in fundamental analysis hold the best-diversified portfolios while investors who rely on their intuitions diversify the worst, suggesting a strong relationship between diversification and overconfidence. Da Costa, Goulart, Cupertino, Macedo and da Silva (2013) design an experiment to measure investor biases and find that although investors exhibit disposition effect, experienced investors do less so. Fuertes, Muradoglu and Ozturkkal (2014) assert that portfolio under-diversification of investors is an expression of overconfidence. They used a dataset from a brokerage house of Borsa Istanbul to conclude that Turkish investors are very underdiversified with on average two shares in their portfolios, implying overconfidence, well below recommended numbers but relatively close to other European market averages. They also state that individuals who trade frequently are better diversified. Bodnaruk and Simonov (2015) study the effect of financial expertise on investment outcomes and find no evidence that financial experts have lower behavioral biases or make better investment decisions than peers. Kumar and Goyal (2015) do a systematic literature review and report that behavioral finance literature confirms that overconfidence,

disposition effect, herding and home bias are common in individual investors. Ateş, Coşkun and Şahin (2016) survey randomly selected 596 investors from Borsa Istanbul and find that most of the investors have a high level of behavioral biases and there is a negative relationship between financial literacy and many behavioral biases. They also emphasize that no matter what efforts are put into increasing the financial literacy of investors, it is not possible to eliminate the behavioral biases completely. They also emphasize that 31% of the Turkish individual stock investors live in Istanbul and the total portfolio value of individual stock investors living in Istanbul (25.170 million TRY) constitutes 61% of the total portfolio value of individual stock investors in Turkey (41.376 million TRY). Hence, people living in Istanbul have a great level of representativeness of Turkish investors. Sahi (2017) argues that behavioral biases are an integral part of human psychology and they are not necessarily always bad. They find that some biases have a positive association with financial satisfaction. Filiz, Nahmer, Spiwoks and Bizer (2018) design an experiment to examine the influence of several behavioral biases on diversification behavior. They report that gambler's fallacy is the main driver of non-optimal and underdiversified portfolio choices. Zahera and Bansal (2018) review the literature and compile 17 types of different behavioral biases that have a significant effect on investment decisions of investors. Costa et al. (2017) conduct a bibliometric analysis and report that overconfidence is the most studied bias in behavioral finance literature. El Harbi and Toumia (2020) study the influence of status quo bias on venture capital investments and reveal that the choice of investment areas depends positively on the previous choices of investors. Hirshleifer (2020) studies behavioral biases of analysts and reports that financial analysts' first impressions of a company have a lasting effect on their future forecasts. Analysts with a first positive

impression set higher price targets and negative impressions set lower price targets and the effects of these first impressions last about 36 months.

2.2 Gamification

Gamification is the application of popular game elements to other areas of activity with the goal of motivating and encouraging participation (Deterding, Dixon, Khaled, & Nacke, 2011). It is gaining popularity among various topics, also as a next generation method for marketing and customer engagement (Hamari, Koivisto, & Sarsa, 2014). Gamification has been proven to be effective in various domains including, but not limited to education, commerce, communication, finance, government services, health, marketing and public engagement (Hamari & Koivisto, 2015b; Sironi, 2016).

Gamification is also gaining importance in financial applications but compared with domains like healthcare or education, it is still relatively in its early days (van der Heide & Želinský, 2021). Stockinger et al. (2015) discuss how mobile apps and gamification impacts financial decision-making, develop an electronic piggy bank and conclude that people favor an app that helps them save money. Palakvangsa-Na-Ayudhya, Pongchandaj, Kriangsakdachai and Sunthornwutthikrai (2017) study a gamified, cashless piggy bank and conclude that gamification increases saving behavior among children. Rodrigues, Oliveira, Rodrigues and Costa (2019) show that using gamification to measure financial literacy helps investors to be informed more about their financial needs and understand the financial products suitable to increase their financial well-being. Bayuk and Altobello (2019) report that gamification improves financial well-being and gamified elements increase motivation to save. Yulius, Neta and Nasrullah (2019) show that providing a

gamified mobile application improves stock market knowledge among young people. Pal et al. (2021) study gamification of financial applications and financial behavior of young investors and report that gamification significantly moderates the influence of financial attitude and financial planning activity on financial management behavior. Inchamnan, Niranatlamphong and Engbunmeesakul (2019) investigate financial literacy in Thailand and find that designing gamified activities increase saving and persuade individuals to change their financial behavior positively. Baptista and Oliveira (2017) study the utilization of gamification in the acceptance of mobile banking services and find that there is a strong relationship between gamification and intention to use mobile banking. They state that gamification is an important facilitator that makes conventional services like banking an interesting and enjoyable experience. Rasco, Chan, Peko and Sundaram (2020) emphasize the importance of financial literacy and mention that there is a lack of good means to deliver this body of knowledge to young people. They propose that gamification is a great tool to impose better financial behavior, especially to the youth. Bitrián et al. (2021) show that gamifying personal finance management applications increase user motivation and perception of ease of use. They imply that individuals develop more favorable intentions toward gamified applications. Chauhan, Akhtar and Gupta (2021) explore gamification in banking and discuss that gamified interfaces can simplify banking products and increase financial literacy. Yau and Wong (2022) state that gamification is a high-potential and low-cost tool to improve financial literacy, especially by improving the financial management knowledge of individuals. Wong, Liu, Meng-Lewis, Sun and Zhang (2022) explore gamification in mobile payments and reveal that the perceived effectiveness of gamification directly contributes to the user attitude.

2.3 Stock market simulation games

Stock market simulation games are special implementations of gamification. They are not just additions of gamified elements into an existing process, but also a great way to simulate real-life investing scenarios. They can be a small teaching experiment in a classroom or a massive, country-wide, realistic game. Older stock market simulation games were based on paper and pen (Branch, 1975). They started as simple tools that require manual work by the instructor to measure and improve financial literacy of students in business and economy classes, but with access to technology and the Internet, grew into more effective tools. Tykocinski, Israel and Pittman (2004) test students' ability to behave in a stock market game and showed that they lack financial literacy and carry strong biases. Harter and Harter (2010) report that students who played a stock market game in a finance course have improved financial literacy over the ones who did not. They also state that students who have previously played the stock market game do much better when they play it again, compared to the other students who play for the first time. Hinojosa et al. (2010) conduct a nationwide randomized controlled trial and assessed the impact of playing a stock market game on student investment knowledge. They conclude that playing a stock market game improves financial literacy of students in all grades. Moffit, Stull and McKinney (2010) conduct an experiment with a stock market game and report that without lectures or assigned readings, students gain significant knowledge of financial markets. Huang and Hsu (2011) study online games and their effectiveness in improving financial literacy. They conclude that integrating financial games, including a stock market game, improves financial literacy of students significantly. Stewart, Houghton and Rogers (2012) conduct tests using a virtual trading room and report significant improvements in student financial literacy.

Niederjohn (2012) assess the results of a stock market game and found that there is a significant increase in financial literacy of randomly selected students. Day (2013) surveys 122 students that played a 10-week stock market simulation game and found that participation in the stock market game has a causal effect on their finance course test score gains. The game survey also concludes that 55% of the students decided to be more careful with money, both findings indicating a direct increase in financial literacy. They also found that students with high gains are more likely to increase their willingness to take a risk, namely developing overconfidence. Da Costa et al. (2013) design a stock market simulation to experiment with two groups, experienced and inexperienced investors. They let them play the game and measure the individuals' exhibition of disposition bias. They find that both groups show disposition effect but more experienced investors do less so. Gill and Bhattacharya (2015) try different types of financial education on students and conclude that a more holistic and hands-on approach, including a stock market game is more effective in improving financial literacy than traditional methods. Goulart, da Costa, Andrade and Santos (2015) design a lab experiment where they measure behavioral biases of participants who trade in incentivized stock market simulations, with the knowledge that their financial behaviors and performance will be either announced to the public or kept private. They find a significant increase in behavioral biases when the investors know that their financial performance will be public. Santo and Martelli (2015) analyze the results of a mutual fund management simulation game and conclude that simulations in general help mitigate opportunistic behaviors and increase financial literacy of the participants. Bhattacharya, Gill and Stanley (2016) mention a 1-week "financial literacy camp" consisting of 83 students, where a stock market game was also a part of the camp. They report an approximately 12%

increase in financial literacy. Liew, Piaw, Zawawi and Bujang (2019) create an experimental stock market game for Malaysian diploma students and find that the group that played the game scored much higher means in a financial literacy test. Dvorackova, Jochec and Tichy (2019) design an experimental simulation game with students and show that participants are exhibiting disposition effect. Cueva, Iturbe-Ormaetxe, Ponti and Tomás (2019) design a stock market simulation game to measure the disposition effect among investors. They report that the most significant predictors of this bias are optimism and the difficulty of recognizing one's mistakes. Smith and Gibbs (2020) conduct a stock market simulation game for business students and show that students who participated in the game earned higher grades and improve their grades much more compared to non-participants. Chapkovski, Khapko and Zoican (2021) run a gamified online trading platform to study investors' risk-taking in a trading environment with several gamified elements and show that gamification motivates investors to take more risks, especially with high-volatility securities. Merl (2021) argues that since insider trading is a very sensitive legal issue, gathering real-life data is very hard if not impossible. Thus, the only viable alternative left is stock market simulation games. Adil, Singh and Ansari (2022) advise policy makers and financial institutions to conduct stock market simulation games to help investors learn about investing in the stock markets and increase their financial literacy.

CHAPTER 3

HYPOTHESIS DEVELOPMENT

Stock market simulation games are laboratory environments that provide a valuable way to build experimental asset market to put financial theories into test in the investment field (Duxbury, 1995). They are also the only viable method for empirical evidence in sensitive topics like insider trading, where gathering real-life data is impossible (Merl, 2021). However, their representativeness of naturally occurring trading, especially differences in behaviors and biases when investors are dealing with real money compared to hypothetical money, assessed only to a very limited extent. Nevertheless, previous research discussing this topic is available on very similar areas in experimental finance. Many characteristics may also limit the representativeness of stock market games, like hypothetical money not gaining interest, lack of sophisticated brokerage fees and absence of corporate actions (like dividend payments). Absence of the possibility to lose real money also promotes high risk taking behavior like buying risky securities to achieve high gain, as there is no real loss in real wealth for wrong financial decisions (Kagan, Mayo, & Stout, 1995; Mandell, 2006). Since investors obviously invest to earn money, investment gains (trading profits) are direct rewards of an investor's decisions, behaviors and actions. Real rewards are shown to produce different behaviors and results compared to hypothetical rewards (Kirby, 1997; Xu, Xiao, & Rao, 2019). Especially hypothetical rewards are linked to impulsive and not well-thought behaviors (Hinvest & Anderson, 2010) while real, high rewards are shown to improve decision quality (Horn & Freund, 2022). There are also recent studies that measure different type of brain activity and suggest that real and hypothetical rewards modulate human

behaviors differently (Kang, Rangel, Camus, & Camerer, 2011; Xu et al., 2018, 2016). Thus, the following hypothesis is proposed:

- Hypothesis 1. Behavioral biases of investors, who simultaneously trade in the real trading environment and the stock market simulation game, are different.

Research derived from trading data to measure behavioral biases in literature has been limited. Furthermore, few studies focus on developing markets. In contrast, Tekçe and Yilmaz (2015) and Tekçe et al. (2016) work on data from Turkey and measure overconfidence, disposition effect, familiarity bias, status quo bias and representativeness heuristic. Their approach is adopted and the following behavioral biases are tested:

- Hypothesis 1a. The level of overconfidence of investors, who simultaneously trade in the real trading environment and the stock market simulation game, are different.
- Hypothesis 1b. The level of disposition effect of investors, who simultaneously trade in the real trading environment and the stock market simulation game, are different.
- Hypothesis 1c. The level of familiarity bias of investors, who simultaneously trade in the real trading environment and the stock market simulation game, are different.
- Hypothesis 1d. The level of status quo bias of investors, who simultaneously trade in the real trading environment and the stock market simulation game, are different.

Most of the literature on stock market simulation games comes from educational sciences where students are the most convenient subjects, but real-life scenarios have

been limited. The idea of using stock market simulation games in finance education go way back to pen and paper days (Branch, 1975), but more widespread use is reported with the emergence of information systems into mainstream use. Studies on students show that they have low financial literacy and carry strong biases (Tykocinski et al., 2004). However, their literacy increase and their investment behavior improve after participating in a stock market simulation game (Gill & Bhattacharya, 2015; Harter & Harter, 2010; Kaiser & Menkhoff, 2020; Santo & Martelli, 2015; Smith & Gibbs, 2020; Stewart et al., 2012). Malesza (2019) also demonstrates that after being exposed to experiments with hypothetical rewards, participants make more informed choices when exposed to real rewards, indicating better financial behavior. So how can a stock market simulation game help mitigate biases and improve financial behavior? The relationship between financial literacy, financial behavior and biases has been studied from various aspects. Fernandes, Lynch and Netemeyer (2014) conduct a meta-analysis of the relationship between financial education, financial literacy and financial behavior and find a statistically significant relationship between them. Dhar and Zhu (2006) report a significant inverse relation between financial literacy of investors and disposition effect, a very well-known behavioral bias. Jonsson, Söderberg and Wilhelmsson (2017) find that different levels of financial literacy have different diminishing effects on disposition effect. Baker et al. (2019) show a significant negative association between financial literacy and behavioral biases. On the other hand, some negative relationship is also reported in literature, arguing that stock market games may trigger unnecessary risk taking behavior (Day, 2013; Kagan et al., 1995; Mandell, 2006), which is linked to behavioral biases (Kiymaz, Öztürkcal, & Akkemik, 2016). Legaki, Karpouzis, Assimakopoulos and Hamari (2021) show that gamification improved learning

outcomes by improving behavior and decreasing biases. Finally, Sivaramakrishnan, Srivastava and Rastogi (2017) suggest that participating in a stock market game improves financial decision-making and investment behavior through gamification and hands-on experience. Thus, the following hypotheses are proposed:

- Hypothesis 2. Participating in a stock market simulation game decreases behavioral biases of investors.
- Hypothesis 2a. Participating in a stock market simulation game decreases overconfidence of investors.
- Hypothesis 2b. Participating in a stock market simulation game decreases disposition effect of investors.
- Hypothesis 2c. Participating in a stock market simulation game decreases familiarity bias of investors.
- Hypothesis 2d. Participating in a stock market simulation game decreases status quo bias of investors.

Finally, how demographics can impact participation in such gamified environments is elaborated. For this, first, existing research on stock market participation as well as participation in gaming is looked into. Previous research shows that market participation is positively associated with demographics such as gender, age, wealth, social status and education level. (Almenberg & Dreber, 2015; Christiansen, Joensen, & Rangvid, 2008; Cole, Paulson, & Shastri, 2014; Conlin et al., 2015; Griffiths, Davies, & Chappell, 2004; Grinblatt et al., 2011; Kimball & Shumway, 2010; Sivaramakrishnan et al., 2017; van Rooij, Lusardi, & Alessie, 2011). Several studies have assessed the demographics of participation in games. King, Delfabbro and Griffiths (2010) argue that a typical game player stereotype is a male in his early twenties, however Paaßen, Morgenroth, & Stratemeyer (2017) challenge this and

attest that the real issue is the invisibility and marginalization of women in the world of gaming. Koivisto and Hamari (2014) find that perceived ease of use of gamified service diminishes as people get older, so they use less technology. In gaming literature, almost every aspect of intention to use gamified systems and participation in games are reported to be correlated with demographics like gender and age (Aydin, 2018; Greenberg, Sherry, Lachlan, Lucas, & Holmstrom, 2010; Hyun et al., 2015; Smohai et al., 2017; Yee, 2006a, 2006b; Yee, Ducheneaut, & Nelson, 2012). Thus, the following hypothesis is proposed:

- Hypothesis 3. Demographics impact participation in stock market simulation games.

CHAPTER 4

METHODOLOGY

4.1 Experimental design

This study utilizes a unique dataset from a mid-sized, independent brokerage house located in Istanbul, Turkey. A simplified high-level order flow diagram of a typical brokerage house or investment bank is shown in Figure 1. There are three scope boundaries. The first one is the investor scope boundary. Before widespread usage of the Internet, individuals had to physically go to the trading rooms or call their agents to submit orders to be executed in the stock exchange. Nowadays, investors use their own devices to log in, check their portfolios and create buy/sell orders over the Internet. Most brokerage houses offer web pages, mobile applications and integrations to third-party applications so that their customers can conveniently trade from anywhere. The second one is the brokerage house scope boundary. The core order management system holds the master data, definitions, customer information and orders. In addition to numerous automated processes, employees also use the system to monitor or manage the system for updating data, changing risk management parameters, processing documents or doing operational work, like accounting and reporting. The orders received from the investors are accepted into the order management system after balance and risk management checks. Then, the orders are formatted and relayed to the stock exchange, either immediately during trading hours, or queued for relaying later if outside stock exchange trading hours. The third one is the stock exchange scope boundary. The stock exchange system receives the request, performs checks and processes it. If it is a new order, it is placed in the order book of the specific stock. If it is an amendment or cancellation, it finds

the order in the relevant order book and if it is not executed (filled) completely, it tries to fulfill the request. A key part of this flow is the matching engine. The matching engine matches buy and sell orders sitting in the order book with the same price. The resulting execution is called a trade. An order will sit in the order book until it is executed (matched with a corresponding order) or expired (mostly at the end of the trading day). Table 1 shows an order book summary example. The lowest possible trading price for this security is 7.31 and the highest is 8.93, as shown in the middle column. In the buy and sell columns, the volume of total orders that are waiting at the respective price level is shown. Supply and demand determine the buy and sell prices. At any point in time where no execution is occurring, the order book is level with a buy and sell price. The lowest-priced sell order determines the sell price and the highest-priced buy order determines the buy price. If the two parties agree on one of the other parties' prices, the orders are matched and a trade occurs. In the example provided, the sell price is 8.13 and the buy price is 8.12. If a buy order with a price of 8.13 or a sell order with a price of 8.12 is submitted, the security will exchange hands at the specified matching price and a trade occurs. This balance is kept until all units with the lowest sell price are bought or all units with the highest buy price are sold. In the example, the selling price will remain at 8.13 until all 739 units at that price level are bought. If no new sell orders at that price level arrive and all 739 units are sold, the balance changes and the new sell price will be set as 8.14.

A modern matching engine in a large stock exchange is capable of doing more than a million matches per second. Any update in the order books, i.e. new orders arriving, orders getting amended/cancelled or a trade occurring; an event is triggered and a new message is pushed to the brokerage house (either directly or by a data vendor, which is omitted in the figure for brevity) through a live price/data feed.

A modern stock exchange system can push more than ten million real-time messages per second through its data feed with latency measured in nanoseconds, resulting in terabytes of raw data per day.

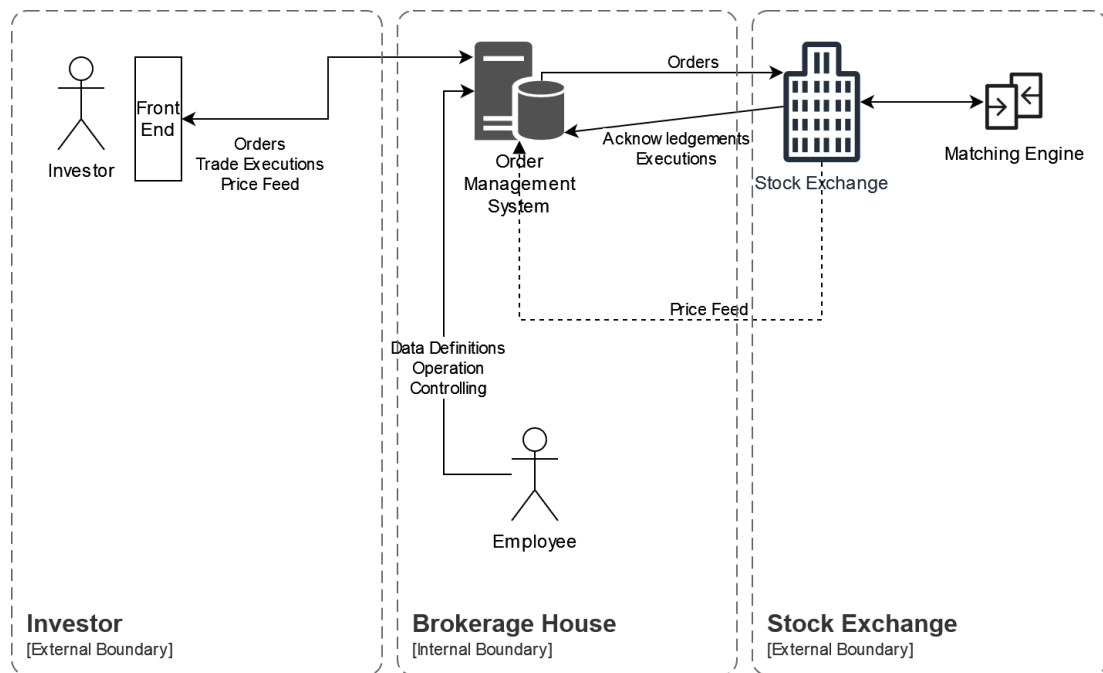


Figure 1. Typical brokerage house order flow

Table 1. Order Book Summary Example

Buy	Price	Sell
	8.93	93729
	8.92	7394
	8.91	948
	8.90	370
	.	
	.	
	.	
	8.15	759
	8.14	846
	8.13	739
3298	8.12	
9584	8.11	
9974	8.10	
	.	
	.	
	.	
3709	7.34	
997	7.33	
48937	7.32	
49349	7.31	

The brokerage house introduced a simulated stock exchange game in 2012 with the purpose of advertising investment services, onboarding new customers by teaching stock market investing and improving the financial literacy of existing customers. Enrollment in the game was completely free and open to everybody even if they did not have an account with the brokerage house, but they had to register with a valid e-mail address. The author was the responsible person who designed and programmed the technical infrastructure of this virtual brokerage house and stock exchange environment. Figure 2 shows the real trading environment side by side with the stock market simulation game environment. Many stock market simulation games have some pitfalls (Kagan et al., 1995); most use closing prices to fill the orders, very few apply corporate actions (like dividends, stock splits, rights issues) and brokerage fees are simplistic but not realistic. To overcome these issues, the stock market simulation game backend uses a slightly modified copy of the exact same order management software (market leader in the region) as the real brokerage house. The maintenance operations team manages this environment exactly like the real system, new securities are defined and all end-of-day batch operations like taxing and brokerage fee calculations are done automatically. A live market data stream feeds the system with live stock market prices and a stock market simulator works in the background, filling the orders immediately when they would have also been filled in the real market. Investors start with an initial cash value of 100000 Turkish Liras (approximately 45870 USD on average between the years 2011-2016) and are able to invest in cash equity (stocks). In summary, the game is a one-to-one simulation of a real trading environment.

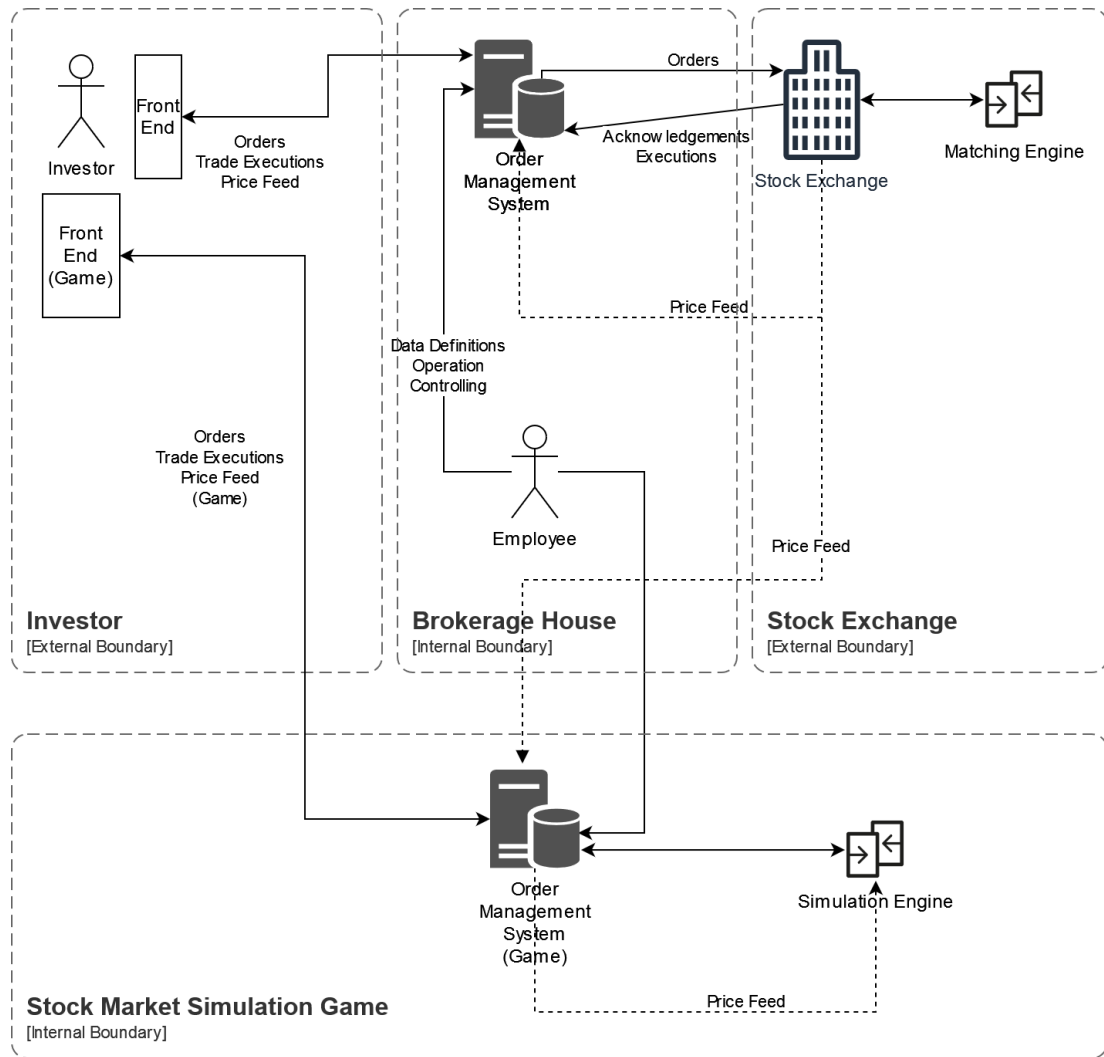


Figure 2. Brokerage house with stock market simulation game order flow

The main components of the stock market simulation game engine (in addition to the core order management system) are as follows:

- i. New user monitor: When a new user is registered, immediately and automatically open investment accounts, transfer 100000 TRY virtual money and send a welcome e-mail containing instructions on how to invest.
- ii. Real system monitor: This subsystem monitors the real trading order management system for changes like risk management definitions and rules, new securities in the market and corporate actions (bonus issues, right issues, dividends) and apply them simultaneously in the stock market simulation game, just as if the investors are

trading in the real stock market. For the sake of brevity, rights issue, a type of capital increase where all or some of the capital is collected voluntarily from the shareholders, is excluded as it involves complex decisions that may even confuse experienced investors.

iii. Market data feeder: Receive live market data from the stock market, update the order management system and trigger events in the respective subsystems.

iv. Trading hours monitor: When at the stock market a trading session is stopped (e.g. due to technical failure, unprecedented event), a security is temporarily closed for trading (e.g. due to important news about the company, unusual trading activity) this monitor takes action and updates the order management system when necessary. When the trading hours end normally (end of the day), this subsystem also triggers the end-of-day batch operations automatically.

v. Order matching engine: Works like the matching engine in the stock exchange but at a much smaller scale. Each new order or a price change coming from the market data feed triggers an event that checks whether there is a waiting order at that price level, provided that there is a trading session going on. Orders coming in after the trading session close are queued for processing the next day. The order management and execution are as close as they can get to the real stock exchange, excluding one limitation: liquidity. In the normal stock exchange, even though the buy and sell orders can match at the same price, there should be enough orders on the other side to completely fill an order. Otherwise, the order gets filled partially. In the stock market simulation game, if the. This does not make a huge difference, as all investors start with 100000 TRY and there is almost always enough liquidity in stocks listed in Istanbul Stock Exchange to cover orders below that amount.

Between years 2012-2016, a total of 61569 individual and anonymous accounts have registered to the stock market simulation game. 43093 (70%) of them have given at least one stock market order. Even though registration to the game was anonymous, all investors had to submit an e-mail address and it is used as the unique identifier to match investors in the real trading environment with the investors in the stock market simulation game.

Table 2 presents information about the customers of the brokerage house (real trading environment). “Real trading data of customers” column presents data of 9487 distinct active customers of the brokerage house. The information regarding trade presented in this column comes from the real trading data, while column “Real trading data of customers who have registered to the stock market simulation game” shows the number of customers who have registered to the game and their real trading data. Matching the e-mail addresses of individuals between the real trading system and stock market simulation game, it is found that 693 of investors are also registered to the game. “Stock market simulation game trading data of customers” column contains the stock market simulation game trading data of the exact same customers in the second column.

The main dataset consists of three different subdatasets. Firstly, all the trading data from the real trading environment between 2011 and 2016 is gathered. Secondly, the trading data is compiled from the stock market simulation game. Lastly, gender, age, wealth, trading experience, and zipcode of all investors are collected and if they participated in the stock market simulation game, their enrollment date.

Table 2. Summary of Trading Data

	Real trading data of customers	Real trading data of customers who have registered to the stock market simulation game	Stock market simulation game trading data of customers
Number of investors	9487	693	693
Number of buys	2856620	383650	13768
Total value of buys (millions)	5512	627	90
Mean buy value	1929	1634	6571
Median buy value	144	151	853
Standard deviation buy	7510	5194	15250
Number of sells	2108803	262964	10999
Total value of sells (millions)	5500	622	79
Mean sell value	2608	2367	7178
Median sell value	280	354	243
Standard deviation sell	8820	6298	20896

** Monetary values represented in USD. Originally were in Turkish Liras, converted to USD with an average exchange rate between 2011 and 2016 of 1 USD = 2.18 TRY*

As the subjects can enroll both in the real trading environment and the stock market simulation game at arbitrary times, trading data is aggregated at monthly frequency. This results in an unbalanced panel data of 693 unique investors and a total of 17598 number of observations to work with for Hypotheses 1 and 2, where stock market

participation dummy is the treatment variable. Example records from this panel dataset is provided in Table 3. Then, to test Hypothesis 3, all 9487 investors in the real system are used and a dummy variable is used to represent whether they have enrolled to the stock market simulation game and if so, when. Example records from this dataset is provided in Table 4.

Table 3. Dataset 1: Panel Data of Investor Behavioral Biases

E-Mail	Month Year	Simulation Registered	Overconfidence Real	Overconfidence Game	DispositionEffect Real	DispositionEffect Game	FamiliarityBias Real	FamiliarityBias Game	StatusQuoBias Real	StatusQuoBias Game
1@...	09.2014	0	-2		1,750037		0,67		-0,017457	
1@...	10.2014	0	-2		2,178577		0,59		-0,09199	
1@...	11.2014	1	-2	-2	1,536383	1,312501	0,74	0,6667	-0,047536	-0,142759
1@...	12.2014	1	-3	-1	0,210628	1,371429	0,8	1	-0,059454	-0,06012
1@...	.	1	.	.	.	.	.	.	.	.
	.		.	.	.	.	.	.	.	.
	.		.	.	.	.	.	.	.	.
1@...	12.2016	1	-4	-2	1,204834	1,400001	0,13	0,6471	-0,053705	-0,376228
2@...	07.2015	0	-1		2,195432		0,29		-0,143785	
2@...	08.2015	0	-1		1,143623		0,8		-0,138766	
2@...	09.2015	0	-2		1,285715		0,7		-0,262338	
2@...	10.2015	1	-2	-3	1,875	1,666666	0,8	1	-0,108138	-0,095238
2@...	11.2015	1	-4	-2	2,333335	0,721803	0,9	0,6667	-0,009568	-0,130434
2@...	12.2015	1	-4	-4	1,11111	0,984615	0,71	0,5714	-0,008695	-0,190476
2@...	.	1	.	.	.	.	.	.	.	.
	.		.	.	.	.	.	.	.	.
	.		.	.	.	.	.	.	.	.
2@...	12.2016	1	-4	-5	1,26984	0,74396	0,55	0,3962	-0,06667	-0,169827

Table 4. Dataset 2: All Investors in the Real Environment with Demographics

E-Mail	Simulation_Registered	Age	Male	Marmara	Southeast	Wealth_Low	Wealth_High	Experience
1@...	0	72	1	1	0	1	0	21
2@...	1	62	1	1	0	0	1	17
3@...	0	45	0	0	0	0	1	20
4@...	1	41	1	0	1	1	0	17
5@...	1	23	1	1	0	1	0	1
6@...	1	20	1	1	0	1	0	1
7@...	0	56	0	0	0	0	1	14
8@...	0	42	0	0	0	0	1	10
9@...	0	29	0	1	0	1	0	5
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.

As mentioned, this experiment is unique in many ways, from experimental design to recruiting subjects. As investors were free to register to the game and try out their chances, anyone could register, join the game or leave the game at any time. There was no fixed time-range to measure, so it is important to group the investors according to their activeness for a deeper understanding on the different type of biases regarding the registration and participation in the stock market simulation game. The Banks Association of Turkey (Türkiye Bankalar Birliği) defines an individual as “active” if they have logged into the banking system at least once in a three-month period (The Banks Association of Turkey, 2021). This is also in line with most of the literature on stock market simulation games from educational sciences, as the experiments involving university students last one semester, which is, without taking into consideration breaks and exams, roughly three months. Thus, the investors who are registered to the stock market simulation game are categorized into three groups, according to their “degree of activeness”. Group 1 includes investors who were active for a relatively short time (less than a month). Group 2 includes investors who are moderately active by involving with the stock market simulation game for at most two periods (six months). Investors participating more than six months in the game are considered in a single group, namely Group 3. An investor is defined active that month if they login to the stock market simulation game at least once and has at least one filled (realized) order in the real trading environment that month. The months investors are considered active are not required to be consecutive. Self-paced e-learning systems provide their users online access to information in their own time, own pace and own location (Moore, Dickson-Deane, & Galyen, 2011). As the stock market simulation game is designed as a non-

supervised, self-paced learning environment, the time spent using it is also flexible.

All investor groups are summarized in Table 5.

Table 5. Investor Groups

Group Number	# of investors	# of observations	Description
1	256	4190	Less active (Less than 1 month)
2	95	2669	Moderately active (Less than 6 months)
3	342	10739	Very active (More than 6 months)

Table 6 presents the demographics of the subjects. “Not Registered to Game” column shows the demographics of real investors who are never registered to the stock market simulation game. “Registered to Game” column represents the demographics of real investors who are registered to the stock market simulation game. “All” column represents all investors. Finally, “Nationwide (2011)” column represents nationwide 2011 investor data of Turkey, taken from the Central Registry Agency of Turkey as reported by Tekçe and Yilmaz (2015). For the sake of comparability, their methodology is also followed when grouping and coding of variables. Out of all 9487 active, real customers in the dataset, 88% are male and 12% are female. While at first glance this might seem uneven, the female percentage only slightly deviates from the nationwide figure of 17%. However, the ratio of female investors who are also registered to the stock market game is extremely unbalanced, only 30 people out of 693 real investors who are registered to the stock market simulation game are female (4.3%). In terms of age, 11% are under 35, 46% are between 35 and 44, 42% are 45 or older. Compared to nationwide data of 26%, 36% and 38% respectively, investors of the brokerage company are older than the national averages.

Interestingly, ages of people who also registered to the stock exchange game are closer to the nationwide investor dataset with 34%, 47% and 19% respectively. Still, investors enrolled to the game are younger than the nationwide data. In terms of wealth, 86% of the investors have a portfolio valued less than 10K, 12% between 10K and 100K, only 2% more than 100K. Compared to nationwide data of 34%, 53% and 13% respectively, investors in the dataset are holding smaller portfolios in their brokerage accounts. One explanation could be that investors may have distributed their assets between different brokerage accounts, so nationwide data combines these distributed portfolios for each customer. Looking at the investors registered to the stock market simulation game, the wealth ratios of 80%, 19% and 1% are more or less consistent with all investors. This means that only 8 comparatively wealthy investors had interest in the stock market simulation game. Trading experience is defined as number of years passed after account opening date. In the dataset, 36% of investors have less than 10 years of trading experience, while 64% have 10 years or more. Compared to the nationwide data of 18% and 81%, it can be concluded that the dataset has less experienced investors, even though they are much older. One explanation can be that the nationwide dataset has data from all banks and brokerage companies and people might jump between them when there is an advantage (better infrastructure, lower commissions, joining bonus). Finally, investors' region of residence are looked into. Marmara region is the most developed region in Turkey, with many industrial cities including, but not limited to, Istanbul. Income, wealth and education level is much higher than the rest of the country. On the contrary, Southeast region is the least economically developed region. The rest of the country is listed under "Others". For all investors, Marmara region is 64%, Southeast region is 1% and the rest is 35%. For investors registered to the stock

market simulation game they are 39%, 2% and 59%, while nationwide dataset lists the percentages as 45%, 3% and 52% respectively.

Table 6. Investor Demographics

			Not Registered to Game			Registered to Game			All			Nationwide (2011) *		
			N	%	Cum. %	N	%	Cum. %	N	%	Cum. %	N	%	Cum. %
Gender	1	Female	1094	12%	12%	30	4%	4%	1124	12%	12%	41095	17%	17%
	2	Male	7700	88%	100%	663	96%	100%	8363	88%	100%	203051	83%	100%
Age	1	< 35	850	10%	10%	235	34%	34%	1085	12%	12%	65025	26%	26%
	2	35-44	4064	46%	56%	326	47%	81%	4390	46%	58%	87352	36%	62%
	3	>= 45	3880	44%	100%	132	19%	100%	4012	42%	100%	91769	38%	100%
Wealth	1	< 10K	7616	86%	86%	551	80%	80%	8167	86%	86%	84092	34%	34%
	2	10K_100K	1013	12%	98%	134	19%	99%	1147	12%	98%	128866	53%	87%
	3	> 100K	165	2%	100%	8	1%	100%	173	2%	100%	31188	13%	100%
Trading Experience	1	< 10 yrs.	3070	35%	35%	370	53%	53%	3440	36%	36%	45420	19%	19%
	2	>= 10 yrs.	5724	65%	100%	323	47%	100%	6047	64%	100%	198726	81%	100%
Region	1	Others	3026	35%	35%	267	39%	39%	3293	35%	35%	126557	52%	52%
	2	Marmara	5662	64%	99%	410	59%	98%	6072	64%	99%	109948	45%	97%
	3	Southeast	106	1%	100%	16	2%	100%	122	1%	100%	7641	3%	100%

* Nationwide data from 2011, Central Registry Agency of Turkey. Retrieved from Tekçe and Yilmaz (2015)

Percentages are rounded to the nearest value

4.2 Hypothesis testing

To test Hypothesis 1 and 2, behavioral biases have to be depicted as a quantitative measure. Proxy variables are strong enablers to be used in place of constructs that are hard to measure (Frost, 1979). They are also very popular in experimental finance literature to operationalize behavioral factors. Dewasiri and Weerakoon Banda (2016) analyzed corporate dividend policy literature and report that 68% of the empirical studies use proxy variables to explain behaviors. While there is a vast amount of literature that explains behavioral biases via surveys, research using trading data to describe investor behavior depend on proxy variables. Many researchers utilize a proxy variable constructed as proportions of losses and gains to describe disposition effect (Brown et al., 2005; G. Chen et al., 2007; Dhar & Zhu, 2006; Odean, 1998a). Barber and Odean (2001) mention firm size and book-to-market ratio as a proxy for corporate risk and gender as a proxy for overconfidence. Tekçe et al. (2016) and Cueva et al. (2019) describe many behavioral biases with different proxy variables calculated from trading data. Thus, this approach is followed to test the first two hypotheses by operationalizing proxy variables calculated from investor trading data to depict the following behavioral biases.

4.2.1 Calculation of Proxy Variables to Represent Behavioral Biases

4.2.1.1 Overconfidence

Overconfidence is one of the most prevalent biases in life that drive people into making irrational decisions (Barber & Odean, 2001). The area of investing, where impacts of nearly every decision is very complex to predict or compute, is certainly not exempt from this. Overconfident investors are known to trade more aggressively (Benos, 1998), overestimate their knowledge about the whole market or a certain

financial instrument (Barber & Odean, 2001), engage in risky portfolio choices and make uninformed trading decisions that results in them losing money (Barber, Lee, et al., 2009; Chuang & Lee, 2006). Many studies in behavioral finance literature mention portfolio diversification as a proxy for measuring overconfidence (Fuertes et al., 2014; Glaser & Weber, 2009; Goetzmann & Kumar, 2008; Hoffmann et al., 2012; Tekçe & Yilmaz, 2015). A higher portfolio diversification indicates a lower level of overconfidence, thus portfolio diversification value is multiplied by -1.

$$OC(Overconfidence) = -1 * PC(Portfolio Diversification) = -1 * \sum_{i=1}^n 1$$

where n is the number of unique stocks in investor's portfolio.

4.2.1.2 Disposition Effect

Disposition effect is a common behavioral bias, signifying the tendency of investors to sell stocks with raising prices early and stocks with falling prices late or hold onto them too long. It is also found to be connected with behavioral traits like difficulty recognizing mistakes and optimism (Cueva et al., 2019). The name comes from the disposition to sell winner stocks too early and holding on to loser stocks (Shefrin & Statman, 1985). Disposition effect is commonly calculated as the ratio between proportion of realized gains and proportion of realized losses (Barber et al., 2007; G. Chen et al., 2007; Cueva et al., 2019; Dhar & Zhu, 2006; Odean, 1998a; Tekçe et al., 2016). Thus, this proxy variable is calculated by matching sell transactions to their calculated purchase cost. For each day a sell transaction takes place, realized gain or loss is calculated for sold stocks by comparing the sell price to their purchase cost. If sell price is higher than the purchase cost, it is considered a gain, else it is considered

a loss. For stocks not sold, the purchase cost is compared to the daily closing price. The higher this value is, the higher the investor is prone to disposition effect.

$$DE(Disposition\ effect) = \frac{PGR}{PLR}$$

where

$$\begin{aligned} PGR(Proportion\ of\ realized\ gains) \\ = \frac{Number\ of\ realized\ gains}{Number\ of\ realized\ gains + Number\ of\ paper\ gains} \end{aligned}$$

$$\begin{aligned} PLR(Proportion\ of\ realized\ losses) \\ = \frac{Number\ of\ realized\ losses}{Number\ of\ realized\ losses + Number\ of\ paper\ losses} \end{aligned}$$

4.2.1.3 Familiarity Bias

Familiarity bias is when investors focus on stocks familiar to them. Familiarity can be of professional proximity, geographical proximity or due to holding information on a particular stock (Massa & Simonov, 2006). It is demonstrated that fear of uncertainty and comfort of familiarity are major drivers of familiarity bias (Kilka & Weber, 2000). While these factors are not easy to measure in experimental design, familiarity can also be simply defined as previous ownership of a certain stock (Tekçe et al., 2016). In other words, if an investor bought a certain stock in the past, that stock becomes more familiar to the investor. Therefore, the proxy variable for familiarity bias is calculated by the number of previously owned stock buy transactions divided by the total number of buy transactions. As the unique stock

market simulation game engine is a mirror of the real trading environment, market and price dynamics in both environments are exactly the same. Thus, previous ownership in both environments are treated equally. A higher previous ownership ratio suggests higher familiarity bias.

$$FB = \text{Previous Ownership Ratio}$$

$$= \frac{\text{\#of previously owned stock buy transactions}}{\text{Total \# of buy transactions}}$$

4.2.1.4 Status Quo Bias

Samuelson and Zeckhauser (1988) suggest that any potential decision has a status quo alternative, in other words, doing nothing. Investors are said to have status quo bias when they choose to do nothing and keep the current situation even when there is a better alternative. Kempf and Ruenzi (2006) argue that investors are prone to status quo bias when making financial decisions. El Harbi and Toumia (2020) further state that in addition to individual investors and mutual funds, venture capital investors also have status quo bias. Investors that are prone to status quo bias are expected to change their portfolios rarely. Following Tekçe et al. (2016), daily portfolio percentage changes are calculated for each day t and each stock i by comparing it to the previous day.

$$\text{Status Quo Bias} = -\text{Portfolio Percentage Change}_t$$

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

A higher portfolio percentage change suggests a lower status quo bias, thus this value is multiplied by -1.

Table 7 gives an overview on the descriptive statics of the proxy variables used. All data are of investors, who have accounts both in the real trading environment and the stock market simulation game. “Pre-treatment real trading data” column depicts the overall real trading data of investors, before they enroll to the stock market simulation game. “Post-treatment real trading data” shows the overall trading data of investors, after they enroll to the stock market simulation game. An initial analysis of the whole sample shows that compared to the pre-treatment mean, post-treatment mean of overconfidence of all investors decreases, while the mean of disposition effect, familiarity bias and status quo bias increase. Table 8 presents the correlations between all the proxy variables, both from real trading environment and the stock market simulation game.

Table 7. Variable Definitions and Descriptive Statistics

		Pre-treatment real trading data				Post-treatment real trading data			
		n = 693, N = 8382				n = 693, N = 9216			
Behavioral Bias	Proxy Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Overconfidence	(Negative) Portfolio diversification	-3.7163	7.0733	-108.0385	0	-4.0040	6.4544	-79.1836	0
Disposition Effect	Proportion of realized gains/proportion of realized losses	0.5427	1.6377	0	30.3269	0.5910	2.1055	0	48.5273
Familiarity Bias	Previous ownership ratio	0.2478	0.2675	0	0.9796	0.2694	0.2774	0	0.9911
Status quo Bias	(Negative) Portfolio percentage change	-0.0424	0.0730	-0.5032	0	-0.0377	0.0531	-0.5031	0

Table 8. Correlation of All Proxies, Real and Game

Proxy Variables	Overconfidence Real	Overconfidence Game	Familiarity Bias Real	Familiarity Bias Game	StatusQuo Bias Real	StatusQuo Bias Game	Disposition Effect Real	Disposition Effect Game
Overconfidence Real	1.000							
Overconfidence Game	0.021***	1.000						
Familiarity Bias Real	-0.321***	-0.052***	1.000					
Familiarity Bias Game	0.000	-0.232***	0.084***	1.000				
StatusQuo Bias Real	0.004	0.030***	-0.481***	-0.072***	1.000			
StatusQuo Bias Game	-0.011**	0.157***	-0.073***	-0.520***	0.119***	1.000		
Disposition Effect Real	-0.242***	-0.010*	0.236***	0.013**	-0.161***	-0.011*	1.000	
Disposition Effect Game	-0.007	-0.276***	0.020***	0.133***	-0.048***	-0.200***	0.003	1.000

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To test Hypothesis 1, behavioral biases of each investor in the real trading environment is compared to the same investor in the stock market simulation game at the same time. As the data is in panel format, a simple t-test would not be feasible. Thus, for each bias, an intercept only regression model without predictors is constructed, clustered by investor, given as:

$$y_i = a + e_i$$

where y_i is the difference between real and simulation bias proxy variables ($y_i = \text{Bias}_{\text{Real}} - \text{Bias}_{\text{Game}}$) to measure whether there is a significant difference between them. Significance of the constant will determine whether there is a significance difference between $\text{Bias}_{\text{Real}}$ and $\text{Bias}_{\text{Game}}$.

For Hypothesis 2, participation in the stock market game is defined as the treatment effect. A difference-in-differences model is used to test whether the treatment results in a significant change in behavioral biases of investors. As every investor registers to the stock market simulation game at different times, a generalized difference-in-differences model suggested by Goodman-Bacon (2018) is used as:

$$y_{it} = \gamma_i + \lambda_t + \delta T_{it} + e_{it}$$

where the dependent variable y_{it} is the proxy for the bias in the real trading environment (thus same as $\text{Bias}_{\text{Real}}$ in Hypothesis 1), γ_i is the cross-sectional dummy representing the investors and λ_t is the time period (month) fixed effect. T_{it} is the treatment dummy, representing participation in the stock market simulation game that month.

To test the third and last hypothesis, a modified version of the model used by Tekçe and Yilmaz (2015) and Tekçe et al. (2016) is chosen. The same independent variables are used for demographics. The dependent variable is chosen as a binary dummy variable which represents whether the investor has participated in the stock

market simulation game. Seven independent variables are used to represent five different measures, namely age, gender, trading experience, wealth (low/high) and region (Marmara/Southeast). *Age* is investor's age when they decide to register to the stock market simulation game and for ones who never registered to the game, their age at the very end of 2016. *Male* is the gender dummy, 0 for female and 1 for male investors. *Trading_Experience* is the number of years the investment account has been open in the real trading environment. There are two wealth dummies, namely *Wealth_{Low}* for portfolio amounts less than 10000 Turkish Liras and *Wealth_{High}* for portfolio amounts higher than 100000 Turkish Liras (Average US Dollar/Turkish Lira exchange rate between 2011 and 2016 was 2.18, therefore the values are, in average, 4587 USD and 45870 USD respectively). Marmara dummy equals one if the investor resides in Marmara, the most economically developed region in Turkey, and zero otherwise. Southeast dummy equals one if the investor resides in Southeast, the least economically developed region in Turkey, and zero otherwise. The dependent variable *Game_Registered* is valued 1 for investors who, at one point in time, registered to the game and 0 for others who have never did so. As the dependent variable is a binary dummy, logistic regression is applied to see which demographic factors affect investors in their decision to register to the stock market simulation game.

$$Game_Registered$$

$$= \alpha Age + \beta Male + \gamma Trading_Experience + \delta_1 Wealth_{Low} + \delta_2 Wealth_{High} + \theta_1 Marmara + \theta_2 Southeast$$

CHAPTER 5

RESULTS

For Hypothesis 1, the significance of the constant in the regression will determine whether there is a significance difference between $Bias_{Real}$ and $Bias_{Game}$. Table 9 presents the results. Note that investors in the sample simultaneously participate the simulation game and trade in the real environment.

Table 9. Hypothesis 1: Difference between Behavioral Biases

	Overconfidence	Disposition Effect	Familiarity Bias	Status quo Bias
Less active (Less than 1 month)	-5.2470 *** (0.0665)	1.0337 *** (0.05121)	0.6765 *** (0.0082)	-0.009612 *** (0.0024)
Moderately active (Less than 6 months)	-9.282609 *** (0.1051)	2.8441 *** (0.2565)	0.6526 *** (0.0090)	-0.08382 *** (0.00221)
Very active (More than 6 months)	-3.343475 *** (0.0823)	1.1211 *** (0.0613)	0.6350 *** (0.0048)	-0.08144 *** (0.0011)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

For all three groups, behavioral biases carried by the same investor in two separate environments, namely real trading system and the stock market simulation game are significantly different. These findings suggest that investors carry different levels of

biases when they trade with real money compared to when they do with hypothetical money. Thus, it is verified that financial behavioral biases of investors are different between the real trading environment and stock market simulation game, supporting Hypothesis 1 and all its subhypotheses. This is in line with previous research suggesting that human behavior might be different with hypothetical rewards compared to real rewards (Hinvest & Anderson, 2010; Kagan et al., 1995; Kirby, 1997; Slovic, 1969; Xu et al., 2018). It is also confirmed that this condition holds for all four biases focused on and for all kinds of investor activeness. But is there a learning curve in terms of mitigating behavioral biases by participating in a stock market simulation game? It is tested with the next hypothesis.

For Hypothesis 2, the generalized difference-in-differences model is run for all three groups. Results are summarized in Table 10. A significant negative coefficient is found for overconfidence proxy in two groups. This means that as investors participate in the game, overconfidence decreases. Overconfidence is observed to be decreasing significantly for less active and moderately active investor groups, the latter observing a bigger decline. Among very active investors, the coefficient is negative but statistically insignificant. The reduction in overconfidence bias is evident for less active and moderately active groups but not with very active investors. Thus, Hypothesis 2a is partially supported. For the disposition bias, a significant negative coefficient is found for the active investors. However, a statistically significant coefficient is not found for less and moderately active investors. Thus, Hypothesis 2b is partially supported. The coefficient of familiarity bias is found to be significant for all types of investors and positively correlated, suggesting an increase in the exposure to the familiarity bias, although diminishing with higher level of activeness. As a decrease in this bias was expected, Hypothesis

2c is not supported. Status quo bias is also observed to be constantly increasing as investors spend more time in the stock market simulation game. The coefficient of status quo bias is found to be significant for all types of investors and positively correlated, increasing as the activeness level increases, contrary to the expectation. Thus, Hypothesis 2d is not supported. Overall, evidence is found partially supporting Hypothesis 2 that for certain behavioral biases participation in a stock game have a positive impact. Yet, that impact varies with the activeness of the investors in the game.

Table 10. Hypothesis 2: Difference-in-differences Model

	Overconfidence	Disposition Effect	Familiarity Bias	Status quo Bias
Less active (Less than 1 month) investors	-0.4509 *** (0.1197)	0.1078 (0.0821)	0.0755 *** (0.0138)	0.0079 ** (0.0036)
Moderately active (Less than 6 months) investors	-0.7660 *** (0.1877)	0.4426 (0.3523)	0.0745 *** (0.0154)	0.0094 ** (0.0039)
Very active (More than 6 months) investors	-0.1686 (0.1121)	-0.1695 ** (0.0692)	0.0579 *** (0.0074)	0.0175 *** (0.0020)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

For Hypothesis 3, a logit model is run (Table 11). Negative and significant coefficients are found for age and experience variables, suggesting younger people with less experience have more tendency to participate in a stock market simulation game. Male dummy variable is significant and has a positive coefficient; suggesting that males are more likely to participate in the game. The dummy variable representing the most financially developed Marmara region is significant with a negative coefficient, while the dummy variable representing the most underdeveloped Southeast region is insignificant. This shows that while investors who live in more developed regions are less likely to participate in the simulation, those who live in the financially underdeveloped regions and possibly could benefit more from a simulation have no significant tendency to participate. Both Wealth_Low and Wealth_High dummies are significant with negative coefficients, implying that people with small or big portfolios are less likely to participate in the game, suggesting investors with average-sized portfolios are more likely to do so. Thus, Hypothesis 3 is supported.

Summary of all hypotheses are provided in Table 12.

Table 11. Hypothesis 3: Logit Model

Independent Variable	Coefficient	Std. Error	p-value
Age	-0.0530 ***	0.0053	< 0.001
Male	1.1792 ***	0.1929	< 0.001
Trading_Experience	-0.0799 ***	0.0076	< 0.001
Marmara	-0.3553 ***	0.0820	< 0.001
Southeast	0.2481	0.2824	0.380
Wealth_Low	-0.6482 ***	0.1065	< 0.001
Wealth_High	-0.8524 **	0.3816	0.025

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 12. Summary of All Hypotheses

Hypothesis	Description	Result
Hypothesis 1	Behavioral biases of investors, who simultaneously trade in the real trading environment and the stock market simulation game, are different.	Supported
Hypothesis 1a	The level of overconfidence of investors, who simultaneously trade in the real trading environment and the stock market simulation game, are different	Supported
Hypothesis 1b	The level of disposition effect of investors, who simultaneously trade in the real trading environment and the stock market simulation game, are different	Supported

Hypothesis 1c	The level of familiarity bias of investors, who simultaneously trade in the real trading environment and the stock market simulation game, are different	Supported
Hypothesis 1d	The level of status quo bias of investors, who simultaneously trade in the real trading environment and the stock market simulation game, are different	Supported
Hypothesis 2	Participating in a stock market simulation game decreases behavioral biases of investors	Partially Supported
Hypothesis 2a	Participating in a stock market simulation game decreases overconfidence of investors	Partially Supported
Hypothesis 2b	Participating in a stock market simulation game decreases disposition effect of investors	Partially Supported
Hypothesis 2c	Participating in a stock market simulation game decreases familiarity bias of investors	Not supported
Hypothesis 2d	Participating in a stock market simulation game decreases status quo bias of investors	Not supported
Hypothesis 3	Demographics impact participation in stock market simulation games	Supported

CHAPTER 6

CONCLUSION AND DISCUSSION

This research attempts to answer whether it is possible to reduce behavioral biases via gamification. For this, a research design is followed, where first the behavioral biases of investors who simultaneously trade in a real trading environment and a stock market simulation game are compared. It is found that levels of all four behavioral biases for each investor are significantly different between the two environments. Then the same dataset is utilized to measure the changes in behavioral biases of investors after participating in a stock market simulation game. Decrease in overconfidence is observed immediately and increasingly with the level of investor activeness. A decrease in disposition effect is observed only among investors with a high level of activeness, suggesting a steeper learning curve. Interestingly, an increase in familiarity bias is observed among all investors, although with a decreasing magnitude with higher level of investor activeness. Similarly, status quo bias gradually increases with more experience in the stock market simulation game. These findings suggest that participating in a stock market simulation game results in an improvement in some behavioral biases, depending on how active the investors were in the game. Finally, importance of demographic factors affecting participation in a stock market simulation game is examined. It is found that age, trading experience, gender, residence region and wealth are associated with the decision to participate in a stock market simulation game.

This research contributes the literature in several ways. First contribution is to the debate on use of simulations in experimental finance literature. Previous studies have shown that stock market simulation games are important tools to test theories in

experimental finance. However, their representativeness of a real trading environment and generalizability of results based on them was controversial. The research methodology of comparing actual and simulated decisions without the weaknesses of an experimental design addresses these problems. The findings show that behavioral biases of investors are different in stock market simulation games and real trading world, and some of the biases in real trading environment can be mitigated by participating in a stock market simulation game. They are also in line with previous research which suggest that absence of the possibility to lose real money in stock market simulation games may promote behaviors that are not normally seen in real trading environments and the possibility of real money gains produce different behaviors compared to hypothetical money gains. These findings will be of interest to experimental finance researchers conducting an experiment and interpreting results from a stock market simulation game. Second contribution is to the behavioral bias literature. As noted in prior studies, participation in stock market simulation games is shown to improve financial decision-making and behavior in investing. This research demonstrates that some behavioral biases of investors can be mitigated after participating in a stock market simulation game. This contributes in several ways to the existing body of knowledge on behavioral biases. The significant decrease in overconfidence suggests that investors are more cautious and risk-averse after participating in the stock market game. However, this effect is seen to be fading over time and is not significant after a long period of participation. Even though the wear-off effect in financial education is not unknown (Amagir, Groot, van den Brink, & Wilschut, 2020), there is also evidence in the literature that investors with overconfidence survive in the long run while others drop out (Wang, 2001). Interestingly, the group of investors who has no significant change in

overconfidence, is the only group where there is a significant decrease in disposition effect. It can be speculated that as investors learn to sell losing stocks faster, their portfolios become not so diversified anymore. Future studies can cast a new light on this inverse relationship between overconfidence and disposition effect. On the other hand, an unexpected increase in familiarity bias is observed for all types of investors, although diminishing with a higher level of activeness. This shows that participating in the stock market game does not provide a decrease in this bias and can be interpreted as investors continuing to stick to their well-known stocks, maybe even more after experimenting with them in the stock market simulation game. Status quo bias is also observed to be constantly increasing as investors spend more time in the stock market simulation game. The change in status quo bias is found to be significant for all types of investors and positively correlated, increasing as the activeness level increases. This can also be interpreted that, as investors spend more time in the stock market simulation game and gain experience in the market, they also become more cautious and start to carry less action bias, which is the tendency to favor action over inaction, directly opposite of status quo bias. Additionally, this finding can also suggest that increase in trading experience results in more long-term investment decisions and less speculative trading decisions. Considering the fact that disposition bias reduces with stock market simulation game experience while status quo bias increases, this would also suggest a decline in herding behavior, which is another behavioral bias (Filiz et al., 2018). To sum up; investors participating in the stock market simulation game show risky behavior, try different trading strategies that are significantly different than how they behave with real money and apparently they learn from this experience, mostly show better investment behavior and then apply their learned behaviors on their future, real investment decisions. The findings

of this research provide insights for understanding the relationship between participation in a stock market game and behavioral biases, which is gaining importance in literature as a significant determinant of financial literacy.

Moreover, there are broad policy implications of this study. Policy makers around the world are already looking for effective measures to increase financial literacy to achieve sustainable development goals (Amagir et al., 2020; Hassan & Hamari, 2020). However, a significant fraction of individuals are reportedly unaware of the existence of basic financial instruments yet alone the existence of a stock market (Guiso & Jappelli, 2005). On the other hand, those investing in financial instruments rarely fully comprehend their mechanics (Stolper & Walter, 2017). Accordingly, behavioral biases of individual investors are a concern for policymakers and market regulators (Baker et al., 2019). This study confirms that stock market simulation games, a specific form of gamification, are effective tools for financial literacy education by reducing behavioral biases and promoting better financial behavior and decision-making. They are also a great way to learn how stock market dynamics work in the comforting self-pace of individual investors. Even though there are some examples around the world (the largest being The Stock Market Game from SIFMA (Day, 2013; Harter & Harter, 2010)), to the best of found knowledge, there is no collective and continuous effort of utilizing stock market simulation games in secondary, higher or further (after-school) levels of education by any policymaker. Loerwald and Stemmann (2016) refer to a need of designing a new environment supporting better financial decision-making, by not just providing traditional educational content, but also different and innovative concepts like incentives, which suggest gamification. In light of the findings and similar research, modern financial education should include stock market simulation games. There is a

benefit for everyone but more pronounced possibly for younger, inexperienced groups from lower income groups and less developed regions. There is also evidence in the literature that the early individuals start participating in the stock market game, the earlier they learn to be more careful with their money (Day, 2013). It is found that young, inexperienced investors are more likely to participate in the stock market simulation game. This finding is in line with technology acceptance and gamification literature (Aydin, 2018) and is promising for introducing stock market games to high-school financial education.

However, significant evidence cannot be found for the participation of individuals from lower-income or less-developed regions, whose financial literacy would presumably be lower (French & McKillop, 2016). Furthermore, these groups and regions typically lack the necessary ICT infrastructure and have lower digital literacy, which could hamper their motivations to participate in the stock market simulation game (Radovanović, Hogan, & Lalić, 2015). Previous research shows that unequal access to digital infrastructure or digital literacy hampers financial literacy and thereof financial inclusion (Sahay et al., 2020). Financial literacy is a driver of financial inclusion, which is on the agenda of most countries concerning the United Nations Sustained Development Goals for sustained economic growth. Hence, continuous efforts from policy makers and non-governmental organizations are needed to provide early financial education by gamification. In this context, it is recommended that stock market simulation games should be introduced in high school education, made standard in higher education and also made more accessible to the average citizen in continuous education programs. These findings show that demand is already there, especially for younger, inexperienced individuals.

This research has also implications for financial institutions. A financial institution providing a stock market simulation game would attract many new customers, even young and inexperienced ones who might have no money now. This will be a wise investment for the firm, as these participants of the game will be potential customers of the future, willing to stay in the familiar ecosystem. On the other hand, for their existing customers, stock market simulation games provide a safe haven to test their risky trading strategies as if they are trading in the real environment. This facilitates better investment decision-making and reduces unnecessary risk-taking with real money, which can result in a total loss. Therefore, stock market simulation games can also reduce potential losses of business by saving inexperienced investors from bankruptcy. Thus it is recommended that investment banks and brokerage houses provide stock market simulation games for both their and customers' benefits. By hosting a stock market simulation game, the brokerage house mentioned in this research was able to increase its customer base. They were even able to reach out to the ones who are doing extremely well in the game and offer a job at the trading desk. On the other hand, this kind of gamification also provides an invaluable tool to marketing departments. In retail marketing, providing tailor-made customer service is essential for customer retention and loyalty. All modern retail business use data mining techniques to model the behavior of their customers (Chen, Chiu, & Chang, 2005). Robo-advisors analyzing the changes in the behavior of an investor in the stock market game can offer new products to that customer in the real trading environment, creating a strong mechanism for upselling. Such as, when a sudden increase in risk appetite is detected, the customer can be provided the opportunity to invest in more risky financial instruments. There is also the possibility to train a machine learning model using the trading behavior of successful investors from the

stock market simulation game and create a mutual fund completely managed by the wisdom of crowds and artificial intelligence. However, the question of whether that would really create wisdom or just herding (della Rossa, Giannini, & DeLellis, 2020), warrants further investigation.

CHAPTER 7

LIMITATIONS AND FUTURE STUDY RECOMMENDATIONS

The findings of this study must be seen in light of some limitations. First of all, the subjects are Turkish investors only. Chosen behavioral biases are also the ones documented in the literature to exist in Turkish investors, yet there are other biases that are documented for other markets. It is known that there are cultural differences such as individualism or collectivism that affect the behavioral biases of investors (Tekçe et al., 2016). Hence, further research is needed to find whether these findings are generalizable to other markets and behavioral biases. Moreover, modeling the exact mechanism of complex topics like human behavior is extremely difficult, especially post-mortem. Hence, this research was not able to document gamification's exact mechanism of action with a trace back to a set of definitive actions from investors. Further research can focus on this by developing a mechanism for the traceability of actions of investors, by collecting timestamped data for every move and modeling them in a complex system. Additionally, this work is the first to analyze and document the change in the behavioral biases of individual investors who simultaneously trade in a gamified environment and real trading environment and it is shown that certain biases decrease after participating in the game. However, it is also found that likelihood to participate in the game differs for socio-economic variables and this intrigues further research questions such as whether the performance of these socio-economic groups differs amongst those who participate in the game and those who have never participated, all else equal. A further study exploring the behavioral biases differences of a matched set of individuals across socio-economic demographics would add value to the literature on

gamification and its role in financial literacy. Moreover, this work focuses more on investment behavioral biases and less on monetary outcomes. Further research should also focus on the effect of change in behavioral biases on monetary gains or losses. Existing literature supports that stock market simulation games are beneficial tools to gain hands-on investment for inexperienced individuals. Evidence is also provided that they are also beneficial for individuals with past investment experience. Comparing the benefits of participating in a stock market simulation game for individuals with no trading experience with the benefits for individuals who are already trading in the stock market would be another valuable contribution to the literature.

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