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Impact of gamification on mitigating behavioral biases of investors

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ABSTRACT

We investigate whether gamification can help mitigate behavioral biases of investors 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, we show that investors have different biases in real versus simulated settings. We find that participating in a stock market game affects 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. We also show 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 governmental bodies that plan to conduct similar experiments and design services promoting better financial decision-making and investment behavior.

1. Introduction

Gamification is gaining popularity as one of the methods to embrace, motivate and educate people to improve financial behavior (Bayuk and Altobello, 2019). There is growing evidence in literature that gamification works (Hamari and Koivisto, 2015). While FinTech companies use gamification as a means of improving financial behavior and thereof access to financial services (Bitrián et al., 2021; Pal et al., 2021; Sironi, 2016), governments explore gamification to achieve sustainable development goals (Hassan and Hamari, 2020). Financial literacy, a set of knowledge and skills necessary to make informed financial decisions, is gaining more significance with governments' focus to improve the welfare of the society through financial education (Corsini and Giannelli, 2021; Koh, 2016; Lusardi and Mitchell, 2014; OECD, 2020; Taylor and 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 and 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 and 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 et al., 2019; Zahera and Bansal, 2018). While determinants of behavioral biases are well documented (de Bondt et al., 2008; Kumar and Goyal, 2015), mainstream research focuses on various methods of measuring them, rather than mitigating them (Costa et al., 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 et al., 2016; Kaiser and Menkhoff, 2020; Smith and Gibbs, 2020; Stewart et al., 2012). Firstly, 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 et al., 2013). Observer-expectancy effect, also called

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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).

Our research differentiates from these studies and presents a unique experimental setting. We use a dataset of 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 us 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, we first test whether level of behavioral biases of investors in stock market simulation game are different from real trading environments, providing valuable insight to researchers who would like to carry out similar experiments. Secondly, we determine how these behavioral biases in real trading environments are affected after participating in a stock market simulation game, evaluating the efficacy of gamification in financial behavior and decision-making. Lastly, we report the demographics of investors who voluntarily enrolled in the stock market game, providing an important starting point to researchers, governments, financial services institutions and their marketing departments on 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, we find that for every case we measure for, 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, we find 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 we observe a significant decrease. This effect becomes more pronounced as the investors' activeness in the simulation increases. However, for the familiarity bias and status quo bias, we find a significant increase. Lastly, we show that gender, age, region, trading experience and wealth factors are important in motivating people to actively join a stock market simulation game. We believe that these findings will especially be of interest to researchers, financial institutions and governmental bodies 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 the paper is organized as follows: We start Section 2 with literature review and present each of the respective hypotheses. Section 3 explains our unique dataset, experiment and the methodology we followed in analyzing it, including our variables and their operationalization. Section 4 presents the results and Section 5 concludes our paper with discussion of the results and their implications.

2. Literature review and 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 et al., 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 et al., 2019). Especially hypothetical rewards are linked to impulsive and not well-thought behaviors (Hinvest and Anderson, 2010) while real, high rewards are shown to improve decision quality (Horn and 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 et al., 2011; Xu et al., 2018, 2016).

Thus, we propose the following hypothesis:

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. We adopt their approach and test the following behavioral biases:

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 come 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 and Bhattacharya, 2015; Harter and Harter, 2010; Kaiser and Menkhoff, 2020; Santo and Martelli, 2015; Smith and 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 et al. (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 et al. (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 et al., 2016). Legaki et al. (2021) show that gamification improved learning outcomes by improving behavior and decreasing biases. Finally, Sivaramakrishnan et al. (2017) suggest that participating in a stock market game improve financial decision-making and investment behavior through gamification and hands-on experience. Thus, we propose the following hypotheses:

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 we elaborate on how demographics can impact participation in such gamified environments. For this, first we look into existing research on stock market participation as well as participation in gaming. Previous research shows that market participation is positively associated with demographics such as gender, age, wealth, social status and education level. (Almenberg and Dreber, 2015; Christiansen et al., 2008; Cole et al., 2014; Conlin et al., 2015; Griffiths et al., 2004; Grinblatt et al., 2011; Kimball and Shumway, 2010; Sivaramakrishnan et al., 2017; van Rooij et al., 2011). Several studies have assessed the demographics of participation in games. King et al. (2010) argue that a typical game player stereotype is a male in his early twenties, however Paazen et al. (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 et al., 2010; Hyun et al., 2015; Smohai et al., 2017; Yee, 2006a,b; Yee et al., 2012). Thus, we propose the following hypothesis:

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

3. Data and methodology

3.1. Data

We use a unique dataset from a mid-sized, independent brokerage house located in Istanbul, Turkey. 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 to 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. Our main dataset consists of three different subdatasets. Firstly, we gather all the trading data from the real trading environment between 2011 and 2016. Secondly, we compile the trading data from the stock market simulation game. Lastly, we collect gender, age, wealth, trading experience, and zipcode of all investors and if they participated in the stock market simulation game, their enrollment date.

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, our 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 in average between 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.

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 we use this as our unique identifier to match investors in the real trading environment with the investors in the stock market simulation game.

Table 1 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, we find 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.

As our subjects can enroll both in the real trading environment and the stock market simulation game at arbitrary times, we aggregate trading data at monthly frequency. This gives us 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 our treatment variable. Then, to test Hypothesis 3, we use all 9487 investors in the real system and include a dummy variable to represent whether they have enrolled to the stock market simulation game and if so, when.

As mentioned, our 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

Table 1
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.

Table 2
Investor groups.

Group #	# investors	# 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)

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, we group the investors who are registered to the stock market simulation game in 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). We consider investors participating more than six months in the game in a single group, namely Group 3. We consider an investor as 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 et al., 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 2.

Table 3 presents the demographics of 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, we also follow their methodology when grouping and coding of variables. Out of all 9487 active, real customers in our 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 our 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 our 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%, we can conclude that our 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, we look into investors' region of residence. 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 3
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.

3.2. Methodology

To test Hypothesis 1 and 2, we have to depict behavioral biases 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. Research including, but not limited to Odean (1998), Brown et al. (2005), Dhar and Zhu (2006) and Chen et al. (2007) utilize a proxy variable constructed as proportions of losses and gains to describe disposition effect. 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, we also follow this approach to test our first two hypotheses by operationalizing proxy variables calculated from investor trading data to depict the following behavioral biases.

3.2.1. Calculation of proxy variables to represent behavioral biases

3.2.1.1. Overconfidence. Overconfidence is one of the most prevalent biases in life that drive people into making irrational decisions (Barber and 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 and Odean, 2001), engage in risky portfolio choices and make uninformed trading decisions that results in them losing money (Barber et al., 2009; Chuang and Lee, 2006). Many studies in behavioral finance literature mention portfolio diversification as a proxy for measuring overconfidence. (Fuertes et al., 2014; Glaser and Weber, 2009; Goetzmann and Kumar, 2008; Hoffmann et al., 2012; Tekçe and Yilmaz, 2015). A higher portfolio diversification indicates a lower level of overconfidence; thus, we multiply portfolio diversification value 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.

3.2.1.2. 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 and Statman, 1985). Disposition effect is commonly calculated as the ratio between proportion of realized gains and proportion of realized losses (Barber et al., 2007; Chen et al., 2007; Cueva et al., 2019; Dhar and Zhu, 2006; Odean, 1998; Tekçe et al., 2016). Thus, we calculate this proxy variable 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

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

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

3.2.1.3. 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 and Simonov, 2006). It is demonstrated that fear of uncertainty and comfort of familiarity are major drivers of familiarity bias (Kilka and 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, we calculate the proxy variable for familiarity bias by the number of previously owned stock buy transactions divided by the total number of buy transactions. As our unique stock market simulation game engine is a mirror of the real trading environment, market and price dynamics in

Table 4
Variable definitions and descriptive statistics.

Behavioral Bias	Proxy Variable	Pre-treatment real trading data n = 693, N = 8382				Post-treatment real trading data n = 693, N = 9216			
		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

both environments are exactly the same. Thus, we treat previous ownership in both environments equally. A higher previous ownership ratio suggests higher familiarity bias.

$$FB = Previous\ Ownership\ Ratio = \frac{\#\ of\ previously\ owned\ stock\ buy\ transactions}{Total\ \#\ of\ buy\ transactions}$$

3.2.1.4. 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), we calculate daily portfolio percentage changes for each day t and each stock i by comparing it to the previous day.

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

A higher portfolio percentage change suggests a lower status quo bias; thus, we multiple this value by −1.

Table 4 gives an overview on the descriptive statics of the proxy variables we use. 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 our 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 5 presents the correlations between all our proxy variables, both from real trading environment and the stock market simulation game.

3.2.2. Estimations

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 we work with panel data, a simple t-test would not be feasible. Thus, for each bias, we construct an intercept only regression model without predictors, 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 = $Bias_{Real}$-$Bias_{Game}$) to measure whether there is a significant difference between them. Significance of the constant will determine whether there is a significance difference between $Bias_{Real}$ and $Bias_{Game}$.

For Hypothesis 2, we define participation in the stock market as our treatment effect. We use a difference-in-differences model 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, we use a generalized difference-in-differences model suggested by Goodman-Bacon (2018) 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 $Bias_{Real}$ 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 our third and last hypothesis, we use a modified version of the model used by Tekçe and Yilmaz (2015) and Tekçe et al. (2016). We use the same independent variables for demographics. We choose the dependent variable as a binary dummy variable which represents whether the investor has participated in the stock market simulation game. We use seven independent variables 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. We have 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. Our 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 our dependent variable is a binary dummy, we apply logistic regression to see which demographic factors affect investors in their decision to

Table 5
Correlation of all proxies, real and game.

Proxy Variables	Overconfidence_Real	Overconfidence_Game	FamiliarityBias_Real	FamiliarityBias_Game	StatusQuoBias_Real	StatusQuoBias_Game	DispositionEffect_Real	DispositionEffect_Game
Overconfidence_Real	1.000							
Overconfidence_Game	0.021***	1.000						
FamiliarityBias_Real	−0.321***	−0.052***	1.000					
FamiliarityBias_Game	0.000	−0.232***	0.084***	1.000				
StatusQuoBias_Real	0.004	0.030***	−0.481***	−0.072***	1.000			
StatusQuoBias_Game	−0.011**	0.157***	−0.073***	−0.520***	0.119***	1.000		
DispositionEffect_Real	−0.242***	−0.010*	0.236***	0.013**	−0.161***	−0.011*	1.000	
DispositionEffect_Game	−0.007	−0.276***	0.020***	0.133***	−0.048***	−0.200***	0.003	1.000

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

Table 6
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)

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

register to the stock market simulation game.

$$\begin{aligned} &Game\_Registered \\ &= \alpha Age + \beta Male + \gamma Trading\_Experience \\ &+ \delta_1 Wealth_{Low} + \delta_2 Wealth_{High} \\ &+ \theta_1 Marmara + \theta_2 Southeast \end{aligned}$$

4. Results

For Hypothesis 1, the significance of the constant in our regression will determine whether there is a significance difference between $Bias_{Real}$ and $Bias_{Game}$. Table 6 presents our results. Note that investors' in the sample simultaneously participate the simulation game and trade in the real environment.

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, we verify 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 and Anderson, 2010; Kagan et al., 1995; Kirby, 1997; Slovic, 1969; Xu et al., 2018). We also confirm that this condition holds for all four biases we focus 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? We test it with our next hypothesis.

For Hypothesis 2, we run the generalized difference-in-differences model for all three groups. Results are summarized in Table 7. We find a significant negative coefficient 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, we find a significant negative coefficient for the active investors. However, we fail to find a statistically significant coefficient 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 we were expecting a decrease in this bias, 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 our expectation. Thus, Hypothesis 2d is not supported. Overall, we find evidence 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.

For Hypothesis 3, we run a logit model (Table 8). We find negative and significant coefficients 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 9.

5. Discussion and conclusion

In this research, we attempt to answer whether it is possible to reduce behavioral biases via gamification. For this, we follow a

Table 7
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)

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

Table 8
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

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

research design where we first compare the behavioral biases of investors who simultaneously trade in a real trading environment and a stock market simulation game. We find that levels of all four behavioral biases for each investor are significantly different between the two environments. We then utilize the same dataset 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, we examine which demographic factors are important for participating in a stock market simulation game. We find that age, trading experience, gender, residence region and wealth are associated with the decision to participate in a stock market simulation game.

We contribute the literature in several ways. First, we contribute 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. Our research methodology of comparing actual and simulated decisions without the weaknesses of an experimental design addresses these problems. Our 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.

Secondly, we contribute 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. Our work 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, we also see that this effect is 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 et al., 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. We speculate 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

Table 9
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

biases, which is gaining importance in literature as a significant determinant of financial literacy.

Moreover, there are broad policy implications of our study. Governments around the world are already looking for effective measures to increase financial literacy to achieve sustainable development goals (Amagir et al., 2020; Hassan and 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 and Jappelli, 2005). On the other hand, those investing in financial instruments rarely fully comprehend their mechanics (Stolper and Walter, 2017). Accordingly, behavioral biases of individual investors are a concern for policymakers and market regulators (Baker et al., 2019). Our 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 and Harter, 2010), to the best of our 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 our findings and similar research, we believe that modern financial education should include stock market simulation games. We think that 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). We find 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, we cannot find significant evidence for the participation of individuals from lower-income or less-developed regions, whose financial literacy would presumably be lower (French and 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 et al., 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, we think that continuous efforts from government bodies and non-governmental organizations are needed to provide early financial education by gamification. In this context, we recommend 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. Our findings show that demand is already there, especially for younger, inexperienced individuals.

Our 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, we recommend 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 our 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, we believe 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 et al., 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 et al., 2020), warrants further investigation.

The findings of this study must be seen in light of some limitations. Our 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. We show that certain biases decrease after participating in the game. However, we also find 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, our 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. We also provide evidence 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.

CRediT authorship contribution statement

Doğaç Şenol: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft. **Ceylan Onay:** Conceptualization, Methodology, Validation, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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