The impact of heuristic and herding biases on portfolio construction and performance: the case of Greece

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Abstract

Purpose – The purpose of this paper is to identify whether heuristic and herding biases influence portfolio construction and performance in Greece. The current research determines the situation among investors in Greece, a country with several economic problems for the last decade.

Design/methodology/approach – A survey has been conducted covering a group of active private investors. The relationship between private investors' behavior and portfolio construction and performance was tested using a multiple regression.

Findings – The authors find that heuristic variable affects private investor's portfolio construction and performance satisfaction level positively. A robustness test on a second group, consisting of professional investors, reveals that heuristic and herding biases affect investment behavior when constructing a portfolio.

Practical implications – The authors recommend investors to select professional's investment portfolio tools in constructing investment portfolios and avoid excessive errors, which occur due to heuristic. The awareness and understanding of heuristic and herding could be helpful for professionals and decision-makers in financial institutions by improving their performance resulting in more efficient markets.

Originality/value – The main contribution of this paper lies in the fact that it is the first study on two major behavioral dimensions that affect the investor's portfolio construction and performance in Greece. The rationale of the current research is that the results are helpful for investors in order to take rational, reliable and profitable decisions.

Keywords Behavioral finance, Heuristic, Prospect theory, Herding, Portfolio factor, Portfolio construction, Portfolio performance, Greece

Paper type Research paper

1. Introduction

An investor, or a finance professional, who designs his portfolio considers various general factors in order to earn better returns and diversify risk. Along with the general factors affecting the investment decision, there are various behavioral biases (like heuristic and herding) influencing investment decision when structuring investment portfolios. Findings from research studies, experimental approaches as well as diagnostic assessments conducted in the field of behavioral finance, are conflicting with Kumaran (2013), Tekce *et al.* (2016), Pikulina *et al.* (2017) and Wei (2017), indicating that investor behavior positively influence investment decision. Others (Kengatharan and Kengatharan, 2014; Massa and Simonov, 2004; Nyamute, 2016 and Galaoritis *et al.*, 2016a) find the influence to be negative, while recent papers (Robotis, 2018; Anderson *et al.*, 2018) find no influence at all. The conflicting results provide a research gap that the current study examines using data from Greece.

The principal aim of this study is to analyze if behavioral factors affect investors portfolio construction and performance in Greece. Investment decisions involve psychological illusions which can be divided in two dimensions (see Table A1): (1) *heuristic* factor (such as representative bias, anchoring, availability bias, gamblers' fallacy and overconfidence), (2) *herding* factor (impact of others buying and selling decision, impact of others asset choices, impact of others investment outlooks and impact of following information from reliable

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media). Hoffmann *et al.* (2013), Khan *et al.* (2017) examined investor's portfolio performance focusing on perceived expectations and return perceptions. A criterion to measure portfolio construction and performance for the current study is the satisfaction level of portfolio performance. In other words, the rate of return of portfolio performance is evaluated by asking investors to compare their current real return rates to both their own expected return rates and the average return rate of the market (Abdin *et al.*, 2017). In order to reach the aims and objectives of this research, we investigate the following two impacts for Greece:

(1) Heuristic variables on portfolio construction and performance.

(2) Herding variables on portfolio construction and performance.

Providing evidence from the behavior of Greek active private investors is interesting and important for several reasons. First, this research provides additional empirical evidence on the growing literature on behavioral finance that demonstrates how a variety of decision-making biases influences investment decision and potential outcomes. Second, investor behavior and portfolio performance have largely been examined in recent studies (e.g. Ramiah *et al.*, 2015; Anderson *et al.*, 2018; Mukherjee and De, 2019, among others) focusing in developed capital markets. The current research determines the situation among investors in Greece, a country with several economic problems for the last decade. Greece's chronic fiscal mismanagement and resulting debt crisis has repeatedly threatened the stability of the Eurozone, imposing investors and finance professionals to sold most of their Greek financial assets. The recession in the Greek economy surpassed even the United States' Great Depression becoming the longest downturn of any advanced capitalist economy ever. Following a recessionary period, Greece is now experiencing a credit recovery with country's borrowing cost hit record low (Greek 10-years bond yield 0.55%) for first time. Greece is firmly back on the radar of investors. The Athens Stock Exchange was the best performing (43.91%) equity market in Europe for 2019, reflecting a new confidence of international investors in Greece's sustainable growth. Across the board, foreign investors are investing in Greek assets from stocks to bonds to real estate, helping to drive foreign direct investment (FDI) into new record. An empirical contribution of this study is to analyze whether the use of heuristic and herding leads to an increase of performance satisfaction, even if investment mood and appetite changes from negative to positive, based on the Greek turnaround story. Third, other studies (Maditinos *et al.*, 2007; Menkhoff and Nikiforow, 2009; Bailey *et al.*, 2010; Cuthbertson *et al.*, 2016 and Wei, 2017), among others, have explored behavioral biases on decision-making of institutional investors like equity managers, fund managers, listed companies, etc. Our study intents to conduct a robustness test on the results of the research by performing the same study on a second group, consisting of finance professionals, contributing to abate the disconnection between academic approach and business reality. Finally, studies such as Mobarek *et al.* (2014), Yang and Zhou (2015) and Strombacka *et al.* (2017) considered some of the investment behavioral biases mainly in the stock markets. This provides a research gap that we fill in by the current research, in the way that we focus not only on a wider range of asset classes but also on a wider range of investors' behavioral biases.

For our data analysis, we used a questionnaire, which follows prior similar studies in the area of behavioral finance. Grinblatt *et al.* (2012) and Cohen and Kudryavtsev (2012) have used the traditional finance measures of risks and returns which may not capture other factors that are not based on market fundamentals but which, nevertheless, affect the individual investor portfolio performance (see also Nyamute, 2016). Our study uses primary data to measure investors' behavior by defining the satisfaction level of portfolio construction performance as a dependent variable. We found that heuristic factor is statistically significant having a positive effect on private investor's portfolio construction and performance. From heuristic factor, overconfidence has the most significant influence on investment decision. We conducted a robustness test of the model used by surveying a second group containing finance professionals. We found that heuristic factor has a positive effect, while the herding factor has a negative one, both statistically significant, on finance professionals who mostly rely on their own predictions for portfolio construction and performance. Our findings provide support and are in line with the related literature.

The main contribution of this paper lies in the fact that it is the first study on two major behavioral dimensions that affect the investor's portfolio construction and performance in Greece. The rationale of the current research is that the results are helpful for investors in order to take rational, reliable and profitable decisions. This study offers insights into investors, which will help them, understand how behavior biases affect portfolio construction and performance, and thus, they may be able to become aware of them and overcome them. Moreover, the findings of this paper will help finance professionals, investment houses, asset management companies and private banking houses to analyze future market trends, understand private investor's behavior when designing products and provide more advice to suit their clients' needs. Finally, the results of this study provide evidence to EU's regulators to enrich Financial Instruments Directive (MIFID ii) in order to facilitate and strengthen investor's protection and improve the functioning of financial markets, making them more efficient, resilient and transparent.

The rest of the paper is organized as follows. Section 2 reviews the literature and hypotheses development. Section 3 describes the data methodology. The next section (Section 4) reports the empirical findings and interpretation of results. The final section (Section 5) concludes the study.

2. Literature review and hypotheses development

Although many factors may influence individual financial decision-making, this paper concentrates on heuristic and herding biases that possibly affect active private investors' investment decisions in constructing an investment portfolio.

2.1 Heuristic factor

The term "heuristic" originally meant "find out" or "discover" (Economou *et al.*, 2011) and is defined as the "rule of thumb", which makes decision-making easier, especially in complex and uncertain environments (Ritter, 2003) by reducing the complexity of assessing probabilities and predicting values to simpler judgments (Tversky and Kahneman, 1974), which may lead toward irrational decisions. In other words, Chandra and Kumar (2012) define heuristics as "the process by which people reach conclusions, usually from available information". People frequently, because of lack of ample time or accurate information, make the mistake of believing that two similar things or events are more closely correlated than they actually are. These heuristics can cause investors commit errors in particular situations.

Tversky and Kahneman (1974) introduced three components belonging to heuristics: representativeness, anchoring and availability, while, Waweru *et al.* (2008) introduced two more components to heuristic theory named gambler's fallacy and overconfidence. These heuristics are usually effective, but they lead to systematic and predictable errors. A better understanding of these heuristics and the biases to which they lead could improve judgments and decisions in situations of uncertainty.

The *representativeness heuristic* was first described by psychologists Amos Tversky and Daniel Kahneman during the 1970s. A sample is drawn from population that is considered highly representative of the population, which can be described as representativeness heuristic. Like other heuristics, making judgments based on representativeness may allow people to make decisions quickly; however, it can also lead to errors. Based on the fact that something is more representative does not actually make it more likely. Tversky and Kahneman (1974) showed that representativeness heuristic is affected by individuals in that when they are asked to formulate judgments under uncertainty, most of them base their decisions on representative information.

According to De Bondt (1998), when we make decisions based on representativeness, we may be likely to make more errors by overestimating the likelihood that something will occur. Barberis *et al.* (1998) is probably among the pioneered studies that modeled representative heuristic into behavioral finance to explain investors' over-reaction and under-reaction in stock markets. Barber and Odean (1999) concluded that representativeness bias has a significant relationship with investment performance and explained that investors prefer of buying assets that are in public media or have experienced high-unanticipated trading quantity. Moreover, Dhar and Kumar (2001) investigated the price trends of stocks bought by more than 40,000 households at a discount brokerage in the US over a five-year period. They found that investors might look at price trends to formulate their trading decisions, consistent with the thinking that the past price trend is representative of the future price trend. Wickham (2003) finds that representativeness bias can hinder the quality of investment decisions. In their (Fiotakis and Philippas, 2004) study on whether Greek mutual fund investors over-react to information during both bull and bear markets. They reveal that investors do not chase previous returns and that they do not hunt based on past superior performance. Similarly, Wu *et al.* (2009) examine investors trading strategies of buying based on past high EPS growth and selling based on past low EPS growth stocks over 4–20 quarters in Taiwan. Little support was found, according to them, for the over-use of representativeness heuristic in the long run. Contrary, Chandra and Kumar (2012) identified in their study of 350 individual investors who made investment decisions and concluded that investment behavior is highly influenced by representativeness and mental accounting.

In their (Bracha and Donald, 2012) study on New York Stock Exchange (NYSE) they found that the representative bias has a positive impact on the investment performance; people who follow the dimensions of this bias are often performed better returns. In another study, Tekce *et al.* (2016) identified behavioral biases among Turkish individual stock investors during 2011 by using transaction data of 244,146 investors. Representativeness heuristic deteriorates wealth, while status quo bias results in higher trade performance. Female, older investors and investors with high portfolio values are more subject to disposition effect and representativeness heuristic. In their study, Kariofyllas *et al.* (2017) examined the implications arising from the effect of representativeness on the London Stock Exchange (LSE). The findings supported the dependence of representativeness bias over time. Another study conducted by Khan *et al.* (2017) using a sample of 454 Malaysian retail investors showed that, in line with the naive reinforcement learning, hot-hand fallacy (the tendency to believe that someone who has been successful in an activity is more likely to be successful again in a new attempt) and representativeness heuristics, investors' excessive reliance on past perceived portfolio returns causes them to display optimism, overconfidence and higher risk attitude. The results lead to the conclusion that the presence of behavioral biases deteriorates financial behavior.

Based on the literature review, when investors follow representativeness heuristic, they keep distance from fundamental asset assessments and usually buy easily accessible assets, generating fundamental anomalies.

Anchoring is a human tendency to rely too much on an initial piece of information (e.g. news, abnormal trading volumes, extreme one-day returns and historical prices) when making investment decisions (Andersen, 2010). That initial piece of information considered to be the "anchor". This "anchor" is the reference point for future investment decisions, expectations or judgments. An anchoring bias can cause an investor to ignore the fundamentals of an asset and pay attention purely on the asset price, leading to an incorrect financial decision, such as buying an overweight asset or selling an underweight asset.

Marsden *et al.* (2008) provide international evidence with respect to the effects of anchoring and representativeness heuristics on analysts' forecast errors in Australia. They concluded that Australian analysts anchored on downwards earnings per share forecast adjustments. Burghof and Prothmann (2009) investigate the possibility of anchoring bias to explain the stock price momentum on the German Stock Market and they find that profits made from momentum strategy are due to anchoring on the past prices in Germany. Bolton *et al.* (2010) note that "many stock ordering decisions are driven by intuition than logic". For several reasons, investors anchor on most remembered assets, unverified information from friends and relatives, etc. when making investment decisions. In addition, Andersen (2010) developed a trading algorithm to test anchoring bias in financial markets to present an exact solution for arbitrary price distributions. Their evidence shows that anchoring bias was found in the market participants' decisions.

Kengatharan and Kengatharan (2014) conducted a survey of 128 investors of Colombo Stock Exchange to study behavioral factors that influence the investment decisions of individual investors. The behavioral factors were herding, heuristics, prospect and market (price changes, market information, past trend of stocks, fundamentals of stocks, customer preference and overreaction to price change). Most of the variables from all factors have moderate impacts, whereas anchoring variable from heuristic factor has high influence and choice of stock variable from herding factor has low influence on investment decision. Shiller (2015) notes that investors are most likely to anchor on the nearest prominent index such as the Dow Jones. Moreover, as Shiller (2015) explains moral anchoring underlies the psychological principle that the larger aspect of human thinking, which leads to action, is storytelling and justification. In another study, Chang *et al.* (2019) explained that investors tend to anchor on day prices in valuating ex-distribution stocks, resulting in a positive association between ex-day returns and adjustment factors. A recent study which was published by Alsedrah and Ahmed (2017) examined the profile of 130 individual stock traders in Saudi Stock Market and attempts to determine the behavioral finance factors affecting the speculative behavior of investors. Anchoring appears to be the main predictor of speculative behavior, followed by confirmation, representativeness and overconfidence.

Based on the previous findings anchoring bias seems to has several implications to investment decision-making.

Availability is a cognitive heuristic bias, also known as mental shortcut and happens when people rely on available information excessively to make their decisions. It occurs when investors assess the likelihood of an outcome based on how quickly and easily the outcome comes to mind (Tversky and Kahneman, 1974). In other words, availability bias is a distortion that arises when an investor judges the quality of an investment based on the use of information, which is most readily available, rather than that which is necessarily most representative.

In asset trading area, this bias indicates the preference of investing in local companies (home-bias) which investors are familiar with despite the fundamental principles for a diversified portfolio. Decision-makers who are suffering from the availability heuristic fail to diversify their portfolio, as they tend to choose investments based on irretrievability rather than a fundamental analysis. In addition, they usually fail to accomplish an appropriate asset allocation and do not choose alternative investments because they limit their investment options.

Frieder (2003) was concerned with how the psychological biases of investors were reflected in trading around earnings announcements. She analyzed order imbalances (buy orders less sell orders) following earnings surprises to determine whether traders invest in a manner that is consistent with the availability heuristics. She tested whether such trading patterns affect returns and uncovered evidence that investors extrapolate past trends in earning performance. Another study, conducted by Massa *et al.* (2005) indicated that individual stock picking decisions are affected by availability bias. People use the availability heuristic in probabilistic situations to avoid risk, which has a negative impact on the decision-making process (Keller *et al.*, 2006), as a result, the market becomes inefficient. Waweru *et al.* (2008) found that availability bias affected the financial decisions of institutional investors trading on the Nairobi Stock Exchange. Khan (2015) also found that availability bias has a significant impact on the investment decisions of individual investors. Fachrudin *et al.* (2017) conducted a study of 120 respondents to examine the influence of heuristic behavior toward investment decision of investor. The results showed that there is a significant influence of representativeness and availability bias toward investment decision. There is no effect of anchoring, gambler's fallacy and overconfidence on investment decision.

After reviewing the relevant literature, some studies show a positive relationship between availability bias and investment decisions, while others show that there is a negative relationship between availability bias and investment decisions, which can lead to wrong investment decision.

The *Gambler's fallacy* is known as the Monte Carlo Fallacy, as its most famous example occurred in a Monte Carlo Casino in 1913. Gamblers' Fallacy arises when an investor inappropriately predicts that a trend will reverse based on the outcome of the event that happened previously when in reality, the probability remains the same. In that case, the investor takes too much risk after a positive prediction that can create a probability of inducing losses. Therefore, Gamblers' fallacy leads toward poor decisions. Many investors often commit Gambler's fallacy when they believe that an asset will gain or lose value after a series of trading sessions with the exact opposite movement.

Shefrin (2002) suggested that the experiences of the investors have an important role in decision-making, i.e. the less experienced is prone to representativeness, while the more experienced investors commit "gamblers' fallacy". The investors while investing rely too much on pieces of information. People excessively rely on strength of information rather than the weight of information (Hirshleifer, 2001). Zielonka (2004) asked 24 financial analysts a number of questions aimed at detecting their ways of making decisions and found out that market "signals" considered by technical analysts are consistent with a number of behavioral biases, including the gambler's fallacy. A study by Johnson *et al.* (2005) provided evidence of a relationship between gambler's fallacy and hot-outcome effect in behavioral finance. The use of the gambler's fallacy heuristic leads investors to predict that an ongoing trend will reverse. The outcomes of the study of 118 participants were: (1) an investor would be more likely to invest, once a stock becomes positive, (2) an individual would be more likely to sell the stock once a stock becomes negative and (3) investor tend to show a preference for purchasing winning stock over losing stock, while investors who wants to sell tend to show a preference for selling losing stock over winning stock.

Rabin and Vayanos (2010) develop a theoretical model to examine the link between the gambler's fallacy and the hot-hand fallacy. They show that because of the gambler's fallacy, an individual who observes a sequence of signals is prone to exaggerate the magnitudes of changes in the state but underestimate their duration. By contrast, they demonstrate that long sequences of similar signals may cause people to believe that a type of "momentum" is present in the underlying state itself and to expect sequence continuation. In another study, Jayaraj (2013) proved that investors affected by Gambler's fallacy are able to anticipate the final rate of return during good or bad conditions in the stock market. According to Loh and Warachka (2012), the post-earnings-announcement drift has a significant time-series component consistent with the gambler's fallacy. Furthermore, Kumaran (2013) investigated 144 investors with prior investment experience and 124 new investors.

Results affirmed that experienced investors from both reference groups apply gambler's fallacy heuristics when deciding on investments.

Overall, the gambler's fallacy is well-documented empirically and theoretically. However, there seems to be little evidence on financial markets, including portfolio decision-making.

Overconfidence is a tendency investor may have to misinterpret the accuracy of the information and overestimate their knowledge levels and their ability in making and evaluating investment decisions. Investors who are overconfident have an excessive optimism and as a result, they usually hold riskier portfolios (Odean, 1998). Overconfidence investors are too confident which usually leads them to underestimate risk, overestimate expected returns, trade excessively and construct poorly diversified portfolios.

Odean (1998) found that overconfidence increases trading volume, volatility and liquidity in markets and reported that traders believe their information is superior to others and they overestimate their abilities. By analyzing trading records for 10,000 accounts, he reported that overconfident traders trade more than rational traders, having lower expected returns. Hence, greater overconfidence leads to greater trading and lower expected returns. Lastly, overconfident traders do not tend to hold well-diversified portfolios because they believe so strongly in their asset picks. Chuang and Soo Lee (2006) analyzed the data of all listed companies on the New York Stock Exchange and American Stock Exchange between January 1963 and December 2001 and found a number of facts. First of all, overconfident investors underreact to public information while overreacting to private information. Second, market gains make overconfident investors trade more aggressively in subsequent periods. Third, excessive trading of overconfident investors in securities markets contributes to the observed excessive volatility. Fourth, overconfident investors underestimate risk and trade more in riskier securities.

Statman *et al.* (2006) found that investors who are overconfident about their valuation and trading skills can explain high-observed trading volume. With biased self-attribution, the level of investor overconfidence and thus trading volume varies with past returns. Finally, they tested the trading volume predictions of formal overconfidence models and found that share turnover is positively related to lagged returns for many months. Moreover, Chen *et al.* (2007) investigated Chinese investors' style of decision-making by including 46.969 individuals and 212 institutional investors in their study and concluded that Chinese investors are poor decision-makers because they are suffering from behavioral biases. In more details, Chinese investors do not sell those stocks whose prices are depreciated, they just sell those stocks whose prices are appreciated, second, the researchers found them overconfident and third, they consider that representative bias is an indicator for future results. Chuang and Susmel (2011) conclude that individual and institutional investors are more aggressive following gains, but individual investors trade more in riskier assets following market gains compared to institutional investors. Furthermore, Menkhoff *et al.* (2013) presented an online-experiment on overconfidence in the context of financial markets. The subject pool consisted of 74 institutional investors, 78 investment advisors and 344 individual investors, all of whom registered users of a large online platform for market sentiment data. The results showed that there were stable differences in overconfidence between the three-investor groups. Moreover, investment experience and age have a significant impact on the degree of overconfidence, which goes surprisingly in opposite direction.

Jlassi *et al.* (2014) examined the effect of overconfidence behavior on dynamic market volatility in global financial markets. Using daily data from 27 countries over 2000–2012, they found that overconfidence is more pronounced for the advanced markets relatively to the emerging ones. With the exception of some Asian and Latin American markets, overconfidence is present in both bull and bear markets. Evidence suggests that overconfidence is the main incentive that triggered and prolonged the global financial crisis in the US market and in other continents. According to Durand *et al.* (2013), personality traits are related to overconfidence and overreaction in the Australian financial markets. In Malaysia, Lai *et al.* (2013) examines the behavior of retail and institutional investors during bull and bear markets and find that both investors are overconfident during these periods. Broihanne *et al.* (2014) interviewed 64 high-level professionals and demonstrated that they are overconfident. They indicated that respondents are overconfident in forecasting future stock prices and demonstrated that the risk they are willing to assume is positively influenced by overconfidence and optimism and negatively influenced by risk perception.

In another study, Kiymaz *et al.* (2016) examined the impact of various personal and objective attributes of 206 finance sector professionals on their risk choices derived from their portfolio allocation and personal wealth data. They found that those with higher expected returns invest more in equities, showing overconfidence. Moreover, Im and Oh (2016) demonstrate that overconfidence investors have inferior control over pride and other positive emotions than investors who are less overconfident. They also show that overconfidence is related to poor performance through the mediating effect of strong emotional reactions. Pikulina *et al.* (2017) tested 114 financial professionals and 111 students and confirmed positive relation between direct measures of overconfidence in one's financial knowledge and choice of investment. The relation between overconfidence and investment is robust to the degree of individual risk aversion, the riskiness of the investment projects and to the changes in incentives structure. Strong overconfidence results in excess investment under confidence generates underinvestment, whereas moderate overconfidence leads to accurate investments. Lately, Lewis (2018) demonstrates that overconfidence significantly reduces the likelihood of customers who seek investment advice and as a result the investment decision-making impact on their long-term financial well-being.

The related literature revels that overconfidence is one of the most dominant heuristic in the area of investment decision leading to market inefficiencies.

Based on previous studies given above, the heuristic factor influences investor's performance. Thus, the current study examines the following hypothesis for Greece:

H1. Heuristic variables significantly influence portfolio construction and performance.

2.2 Herding factor

Herding behavior may be defined as the process where market participants imitate each other and/or base their decisions upon the actions of the previous decision-maker (Hwang and Salmon, 2004). When investors have little time to make investment decisions, they are more likely to follow others than to interpret the information they receive. There can be different reasons for herding by different types of investors. For example, individual investors may demonstrate herding behavior by following other investors, large group or noise traders before making investment decisions. Also, institutional investors herd on their past experiences or their previous decisions on investment; in some cases, they imitate the decisions of other institutional investors in order to protect their compensation and reputation concern (Kumar and Goyal, 2015). In the perspective of behavior, herding can cause some emotional biases, like the impact of imitating others trading asset choices, buying or selling decisions, asset allocation, the impact of following others investment outlooks, the impact of following information from reliable media instead of following own beliefs and information.

Chang *et al.* (2000) presented two models for testing the herd and investor's behavior in various international markets (USA, Taiwan, South Korea, Hong Kong and Japan) for the period 1964–1997. They found herding in Japan, South Korea and Taiwan. Hwang and Salmon (2004) employed cross-sectional variance to evaluate if there is heading effect toward particular sectors in the markets (US and South Korean) including the market index and separate such herding from common movements in asset returns induced movements in fundamentals. They found that herding toward the market shows significant movements and persistence independently from the given market conditions and macro factors. In addition, they found evidence of herding toward the market portfolio in both bull and bear markets. Moreover, Caparrelli *et al.* (2004) using data from the Italian Stock Exchange propose that investors are impacted by herding effect and tend to move in the same flow with the others in extreme market conditions. In another study, Economou *et al.* (2011) examined herd behavior in extreme market conditions using daily data from the Greek, Italian, Portuguese and Spanish stock markets for the years 1998–2008. Moreover, they examined the existence of asymmetric herding behavior associated with market returns, trading volume and return volatility. Along with this, they also investigated the presence of herd behavior during the global financial crisis of 2008. The results of the study showed that herding is found to be stronger during periods of rising markets in these stock markets. More so, Spyrou (2013) indicates that research studies are still lacking in the area of decision-making, such as retail and institutional investors and domestic and foreign investors.

In their study, Mobarek *et al.* (2014) examined country specific herding behavior in European liquid constituent indices for the period of 2001–2012. They documented significant herding behavior during crises and asymmetric market conditions. Particularly, herding effect is pronounced in most continental countries during the global financial crisis and Nordic countries during the Eurozone crisis. However, PIIGS countries are the victims in both crises. The study also concluded that common herding forces exist across a large number of markets in Europe, and they are highly related within similar types of markets. Demirer *et al.* (2014) analyzed daily price data on 305 ADRs from 19 countries to examine herding behavior in the market for ADRs within country-based portfolios by providing evidence from sector-based portfolios. They found that there is significant evidence of herding behavior in the market for ADRs from Chile only regardless of alternative model specifications. On the other hand, they found significant effect of the Asian crisis and the recent credit market crisis on herding behavior in ADR issues from Korea and the UK, respectively, suggesting a link between market crisis periods and herding behavior. Moreover, Choi and Skiba (2015) using data from 41 countries document evidence for institutional investors' wide-spread herding behavior in 41 countries, especially in low levels of information asymmetry markets. Further, Galaoritis *et al.* (2016b) tested and provided original evidence on herd behavior in European government bond prices. They utilized a commonly employed methodology to test for return clustering and, overall, they found no evidence of investor herding either before or after the EU crisis. Further tests reveal that during the recent financial crisis there were indeed herding spill-over effects running, however, with a direction from the European countries with no financial difficulties (Northern European markets) to the financially troubled European markets (Southern European markets). Cuthbertson *et al.* (2016) surveyed and critically evaluated the literature on the role of management effects and fund characteristics in mutual fund performance fund manager behavioral biases and the impact these have on risk taking and returns. Managers display home bias, herding and disposition effect overconfidence which leading them to increases risk taking and turnover. There is strong evidence that poor performance persists for many of the prior "loser" portfolios of funds. Nyamute *et al.* (2016) determined the contribution of investor behavior in influencing investor portfolio performance at the Nairobi Securities Exchange by using a sample of 385 individual stock investors. The overall model was statistically significant indicated that investor behavior influences portfolio performance with herding and disposition effect having a positive effect on portfolio performance, while overconfidence has a negative effect on performance.

Economou *et al.* (2016) investigated herding behavior in the Athens Stock Exchange focusing on the recent crisis period. They employed a survivor bias free dataset of all listed stocks from 2007 to May 2015. The empirical results indicate the presence of herding under different market states. Employing the quantile regression method, there were herding in the high quantiles of the cross-sectional return dispersion. However, Li *et al.* (2017) reveals that both retail and institutional investors pay close attention to one another's trades in forming a consensus. In addition, they also document three important findings on the differences between retail and institutional investors. First, institutional investors trade more selectively when compared with retail investors; second, while institutional investors make investment decisions after rigorous analysis, retail investors rely on public information for their trades, as they are influenced by market sentiment and attention-grabbing events; third, while institutional investors react asymmetrically to up- and down-market movements, retail investors are less concerned about up- and down-market movements. Moreover, Guneya *et al.* (2017) found herding only on a small number of occasions in US and South African markets.

Recently, Robotis (2018) examined whether the trading behavior of exchange-traded funds (ETFs) is biased by any herding effect. Return data of a sample of 66 and 34 large-cap and small-cap ETFs, respectively, are used over the period 2012–2016 to assess whether these funds herd and whether herding is more pronounced during extreme markets, during down markets and during days with extreme trading activity and volatility. The results show that herding is not the case for ETFs. However, some evidence is obtained on a decreasing return dispersion among ETFs on days with negative market returns. Trading activity seems not to induce herding.

Based on the review of the literature, some studies show positive relationship between herding and investment decision, while others show no herding effect. In addition, there are differences on herding between investors and practitioners. Thus, the current study examines the following hypothesis for Greece:

H2. Herding variables significantly influence portfolio construction and performance.

2.3 Portfolio construction and performance

A portfolio is a collection of assets that can include cash equivalents, bonds, stocks, commodities, currencies, mutual funds, exchange-traded funds, etc. Individual investors in managing their portfolios are responsible for building and maintaining an appropriate investment mix for a given risk tolerance. Key variables for any portfolio management strategy involve asset selection asset allocation, diversification and rebalancing rules. Other portfolio variables that are not included in behavioral factors, as they are external factors, are frequency of portfolio review, time horizon and exogenous events. Finally, there are different risk investment styles like low, medium and high that affect portfolio performance differently. Markowitz portfolio theory supposes that investor's decisions are made on the basis of "risk return trade – off" without any behavioral influence. However, investors make rational decisions influenced by various behavioral biases and as a result, portfolio risk and return is affected.

Optimizing portfolio selection, which considers investors' behavior, was first proposed by Shefrin and Statman (2000) through the behavioral portfolio theory (BPT). The theory suggests that investors build their portfolios based on their own belief, behavior and perceptions of the market performance. Investors construct their portfolios using a multi-layered pyramid called mental accounts (De Bondt *et al.*, 1985) with the corresponding aspiration levels and risk attitudes for each layer. BPT emphasizes the role of behavioral preferences in investors' portfolio choices.

According to Savage (1954) rational portfolio theory, investors should only care about the expected utility of their portfolios and not about the specific portfolio components. In contrast, a tendency of investors to split up their investments into a safe account, designed for securing the wealth level and a risky account for speculation is often observed (Rockenbach, 2004). Barber and Odean (1999) emphasize that investors are impacted by events in the markets which grab their attention, even when they do not know if these events can result to positive investment performance. Siebenmorgen and Weber (2004) examined the effect of different investment horizons on investors risk behavior. Their study was interested both in participant's risk perceptions and in their asset allocation behavior. They found significant differences between short-term and long-term risk perception. Both the estimated volatilities and the subjective risk assessments depend on the given investment horizon.

Agnew and Szykman (2005) in two experiments tested how three common differences among defined contribution plans (the number of investment choices offered, the similarity of the choices and the display of the choices) lead to varying degrees of information overload. The findings suggested that the success of certain plan features depends strongly on the financial background of the participant. They found that low-knowledge individuals opt for the default allocation more often than high-knowledge individuals. Further, Waweru *et al.* (2008) identifies some market factors as having impact on investor's decision-making: price changes, market information, past trends of assets, customer preference, over-reaction to price changes and fundamentals of underlying assets. Normally, changes in market information, fundamentals of the underlying asset and asset price can cause over/under-reaction to the price change. These changes are empirically proved to have the high influence on decision-making behavior of investors.

Moreover, Oehler *et al.* (2008) analyze the composition of 102 funds whose assets exceed 100m euro in each year, actively managed by the five biggest German mutual fund companies by hand collecting data from annual reports in the period 2000–2003 and came up with convincing empirical evidence of home biased portfolio selection in this duration. Furthermore, bounded rationality of private investors appears to drive suboptimal portfolio selection. The behavior and skill of mutual fund managers seems not to influence the overall home bias. Cohen and Kudryavtsev (2012) used questionnaires completed by MBA finance students to test the degree of investor's rationality when constructing a portfolio. They found that with respect to stock decisions, irrationality cannot be established. Investment in stocks was found to be influenced by expectations, past experience in the capital market and knowledge about the past performance of selected market indices. With respect to corporate bonds expectations about interest rate changes influenced the decision to invest in those bonds, as did past experience in the capital markets. In another study, Cao *et al.* (2017) analyzed a large dataset of private banking portfolios in Switzerland of a major bank with the unique feature that parts of the portfolios were managed by the bank, parts were advisory portfolios. To correct the heterogeneity of individual investors, they applied a mixture model and a cluster analysis. The results suggest that there was indeed a substantial group of advised individual investors that outperforms the bank-managed portfolios, at least after fees.

Research findings suggest that individual investor biases may have a significant role in determining individual decision-maker's financial performance and as a result financial satisfaction. Financial satisfaction is the feeling that investors' certain financial goal is accomplished, in the form of fulfilling that important desire. The measure of financial satisfaction used in this study was based on a multiple-item questions scale that consisted of various dimensions on which the individuals had to indicate their financial satisfaction level. Over all, behavioral biases are becoming an integral part of decision-making process because they heavily influence the investors' performance satisfaction level.

3. Data and methodology

This study attempts to empirically examine whether and how heuristic and herding factors drive private investors decisions regarding portfolio construction and performance satisfaction level.

3.1 Questionnaire design

To collect data, a structured questionnaire (see Appendix 2) was constructed and used as the main survey instrument which were adapted mainly from prior studies (Amenc *et al.*, 2011; Kengatharan and Kengatharan, 2014; Nyamute, 2016) in the area of behavioral finance. An extensive pretesting and a pilot study took place in an attempt to improve the format of the questions.

The questionnaire was divided into three sections. The first section aims to elicit information about the investor's type of investment, investment objective and financial information sources used by the investor, together with some basic demographic questions. The second section aims to measure the effect of behavioral factors (heuristic and herding) to portfolio construction and performance. The last section is based on questions about investment performance satisfaction level along with the absolute portfolio returns from years 2015–2019. Most of the responses were measured on a five-point Likert scales (1 = "strongly disagree," 5 = "strongly agree").

The questionnaires have been constructed based on the research framework published by Kengatharan and Kengatharan (2014), in order to analyze the impact of behavioral biases on investors' portfolio construction and performance in Greece. The questionnaire was translated into the local language where necessary. The Cronbach alpha statistic has been used to determine the degree of consistency among the measurements of each item. For this research, overall, the Cronbach's alpha test is 0.66, which means that the questionnaire indicates an acceptable level of reliability.

3.2 Sample description

Convenience sampling technique along with probability sampling were used to collect data from active private investors. Stratified random sampling allowed us to stratified the population by a criterion of the market share and then choose random cluster sampling to select participants randomly that are spread out geographically. Stratified sampling ensures that the sample is distributed in the same way as the population (Bryman and Bell, 2007).

The total target active private investors' population of this study is approximately 3,800. The recommended sample size of the study should be 116 private banking investors in order to be representative with a margin error of 9% and confidence level of 95%. The selected sample contained private customers of two private banking houses, two stock brokers' houses and a personal banking department of the second largest bank in Greece.

The study took place from 1st June 2020 to15th September 2020. The investor's questionnaires were distributed through their relationship managers either via a printed copy or e-mail, along with a confidentiality letter. The total number of questionnaires returned was 135.

3.3 Models and variables

We run multiple regression analysis to reveal which of the variables have the most and least influence on satisfaction level of portfolio construction and performance (see Figure A1). Our dependent variable is the level of satisfaction of portfolio construction and performance (*PCP*) measured by the overall investment decisions assessments for the last five years. Three items from the questionnaire studied the level of satisfaction followed by Waweru *et al.* (2008), Kengatharan and Kengatharan (2014) and Abdin *et al.* (2017). We use the following regression Eqn (1):

$$PCP = a + \beta_1(H) + \beta_2(HER) + \varepsilon \tag{1}$$

where, *PCP* is the dependent variable *H and HER* are vectors of independent variables explained below. *H* refers to the set of questions pertaining to heuristic variable and *HER* refers to the set of questions pertaining to herding variable. The terms α (constant) and β (regression coefficient) are parameters to be estimated and ε is the error term. The operationalization of the model factors is presented in Table 1.

Furthermore, a multiple regression analysis was conducted to identify which heuristic variable influence portfolio construction and performance satisfaction level most based on the following regression Eqn (2):

$$PCP = a + \beta_1(RE) + \beta_2(AN) + \beta_3(AV) + \beta_4(GA) + \beta_5(OV) + \varepsilon \quad (2)$$

where, *PCP* is the dependent variable *RE, AN, AV, GA* and *OV* are vectors of independent variables. *RE* refers to the set of questions pertaining to representativeness variable, *AN* refers to the set of questions pertaining to anchoring variable, *AV* refers to the set of questions pertaining to availability variable, *GA* refers to the set of questions pertaining to gambler's fallacy variable and *OV* refers to the set of questions pertaining to overconfidence variable. The terms α (constant) and β (regression coefficient) are parameters to be estimated and ε is the error term.

4. Results and discussion

4.1 Findings for private investors

Based on the demographics questions of the private investors surveyed about 86.7 % are male, while 13.3% were female. Over 50 years old is the 64.4% of the respondents. Most of the respondents (74.1%) are married. Most of the respondents (45.9%) have a bachelor degree, while 41.7% have full-time employment. The respondents (57.8%) have more than 15 years of experience which is very important. About the breakdown of their portfolios "cash is the king" with 22.6% allocation. The primary investment objective of the investors (39.3%) is income and growth, while their investment horizon is more than three years (48.1%) which is very rational. Most of the respondents (38.1%) follow their financial advisor regarding their investment decision. Lastly, when the value of investors' portfolios falls more than 10% half of them (54.1%) stay calm and just wait, which means that they do not follow herding bias. Table 2 presents all the details on demographics of private investors responses.

To establish the relationship between the independent variables and the dependent variables, an inferential analysis using SPSS software was conducted which involved a correlation analysis, coefficient of determination and a multiple regression analysis. The data collected for this study were normal and it is shown in Table 3. The values of skewness are between the acceptable range (−1 to +1) and values of kurtosis also are between the acceptable range (−3 to +3).

We used correlation matrix to analyze the relationship between our variables. The statistics of Table 4 demonstrates a low-positive (0.283) significant relationship between heuristic and *PCP* (portfolio construction and performance satisfaction level). Herding bias

Variable	Operationalization
PCP Portfolio construction and performance	The average score (five-point Likert scale) of the answers of the questions used to measure investors/finance professionals' portfolio assessment will be embedded to the model Kengatharan and Kengatharan (2014), Abdin *et al.* (2017)
H Heuristic factor	The average score (five-point Likert scale) of the answers of the questions used to measure heuristic bias will be embedded to the model
HER Herding factor	The average score (five-point Likert scale) of the answers of the questions used to measure herding bias will be embedded to the model

Table 1.
Model factors

		%
Gender	Male	*86.7*
	Female	13.3
Age in years	30 and below	3.7
	31–40	8.9
	41–50	23.0
	Over 50	*64.4*
Marital status	Single	15.6
	Married	*74.1*
	Other	10.4
Academic background	High school and lower	8.2
	Undergraduate	17.0
	Bachelor	*45.9*
	Master	25.9
	PhD	2.0
	Other	1.0
What is your main source of regular income?	Retirement benefits	21.4
	Self-employment	3.9
	Full employment	*41.7*
	My own company	25.2
	Other	7.8
Your investment experience is?	Less than five years	4.9
	5–10 years	15.7
	10–15 years	21.6
	More than 15 years	*57.8*
What type of investment you keep in your portfolio?	Cash	*22.6*
	Bonds	18.5
	Mutual Funds	18.9
	Stocks	19.1
	Forex	8.5
	ETFs	3.6
	ADRs	0.0
	Commodities	1.5
	Derivatives products	1.3
	Insurance products	5.5
	Other	0.6
What is your primary investment objective?	Preserve capital (savings)	20.0
	Income	31.9
	Income and growth	*39.3*
	Maximize growth	8.9
What is your horizon to achieve your investment objective?	None	19.3
	Less than 1 year	11.9
	More than 1 year but less than 3 years	20.7
	More than 3 years	*48.1*
Which of the following sources is most important for your investments?	Fundamental analysis	21.3
	Technical analysis	17.6
	Media & Internet	18.4
	Friends and family	4.5
	Financial Advisor	*38.1*
How would you react if the value of your portfolio fell by more than 10% in any year?	I would consider of redeeming all my assets	4.4
	I would consider of changing my investment strategy	25.2
	I would wait	*54.1*
	I would buy more to lower the average cost	16.3

Table 2.
Demographics of private investors

has very low positive (0.062) not significant relationship with the *PCP*. Finally, heuristic variable has low-positive (0.308) significant relationship with herding variable.

The research hypotheses were tested by using regression analysis. The significant value is 0.004 (see Table 5), which shows that our research model is significant. R^2 measures the proportion of variation in the dependent variable (*PCP*) that is explained by the variations in independent variables (heuristic, herding). Adjusted R^2 gives the value after adjusting the error term. The adjusted R^2 is 6.7%, which means that the independent variables contribute about 6.7% to portfolio construction and performance satisfaction level, while other factors

N = 135	Minimum	Maximum	Mean	Std. deviation	Skewness	Std. error	Kurtosis	Std. error
Heuristic	2.516	3.933	3.221	0.269	0.140	0.209	0.149	0.414
Herding	1.500	4.000	2.952	0.540	−0.198	0.209	−0.399	0.414
PCP*	1.000	5.000	3.331	0.739	−0.286	0.209	−0.114	0.414

Note(s): *PCP = Portfolio Construction and Performance Satisfaction Level

Table 3.
Descriptive statistics

N = 135		Heuristic	Herding	PCP
Heuristic	Pearson correlation	1		
	Sig. (2-tailed)			
Herding	Pearson correlation	*0.308***	1	
	Sig. (2-tailed)	0.000		
PCP	Pearson correlation	*0.283***	0.062	1
	Sig. (2-tailed)	0.001	0.475	

Note(s): **Correlation is significant at the 0.01 level of certainty (2-tailed)

Table 4.
Correlations

Model Summary[b]

Model	R	R^2	Adjusted R^2	Std. error	Dubin-Watson
	0.284[a]	0.081	*0.067*	0.714	1,607

Note(s): a. Predictors: Heuristic, Herding b. Dependent Variable: PCP / N = 135

ANOVA[a]

Model	Sum of sq	df	Mean sq	F	Sig
Regression	5.896	2	2.948	5.780	*0.004*[b]
Residual	67.325	132	0.510		
Total	73.221	134			

Note(s): a. Dependent Variable: PCP b. Predictors: Heuristic, Herding / N = 135

Coefficients[a]

Model	Unstandardized coefficients B	Std. error	Beta	t	Sig
Constant	0.868	0.750		1.158	0.249
Heuristic	*0.799*	0.241	0.291	3.318	*0.001*
Herding	−0.038	0.120	−0.028	−0.316	0.753

Note(s): a. Dependent Variable: PCP / N = 135

Table 5.
Regression analysis: Eqn (1) for active private investors

not studied in this research contribute 93.3%. Durbin Watson statistic is 1.607, which measures the auto correlation between independent variables. Since the value lies between to 1.5 to 2.5, there is no problem of serial correlation. A multiple regression analysis was conducted to identify which behavioral variables influence portfolio construction and performance satisfaction level of active private investors in Greece.

The regression Eqn (1) for active private investors becomes:

$$PCP = 0.868 + 0.799(H) - 0.038(HER) \ + \varepsilon$$

Based on the regression equation, taking all the above variables constant at zero, the portfolio construction and performance satisfaction level (*PCP*) would be 0.868. Table 5 shows some important statistics regarding the independent variables and their eligibility in impacting the dependent variable. According to the statistics, the beta value of heuristic bias is 0.799 which means that 1 unit change in heuristic impacts 0.799 units change in the portfolio construction and performance satisfaction level. As a result, when heuristic is shown by active private investor, portfolio construction and performance satisfaction level is also affected. Its *t* value is 3.318, so the variable is significant. The significance value is 0.001, which means that heuristic variable has a significant positive impact on portfolio construction and performance satisfaction level. This finding is consistent with the results from the study of Chen *et al.* (2007), Chandra and Kumar (2012), Tekce *et al.* (2016) and Alsedrah and Ahmed (2017), who found heuristics factors to affect investors behavior. In addition, the results of Khan's *et al.* (2017) study led to the conclusion that the presence of heuristic bias like representativeness and overconfidence deteriorates financial behavior. Lastly, our result confirms partly Fachrudin *et al.* (2017) study, who found significant influence of representativeness and availability bias, but no effect of anchoring, gambler's fallacy and overconfidence on investment decision.

The beta value of the second variable (herding) is −0.038, which means that 1 unit change in herding decreases 0.038 change in portfolio construction and performance satisfaction level. Herding variable has significance value higher than 0.05, indicating that herding bias do not have any influence on portfolio construction and performance satisfaction level of active private investors. This finding is supported by the study of Galaoritis *et al.* (2016a), who found initially no evidence of herding on equity prices; however, they found significant evidence of herding for high liquidity stocks. In addition, our result is supported by the resent study of Robotis (2018), who examined a sample of ETFs and found no evidence of herding. Contrary, our findings are not consistent with the study of Economou *et al.* (2016) and Nyamute *et al.* (2016), who indicate the presence of herding on different market states.

The results of our study imply that heuristics contribute positively to portfolio construction and performance satisfaction level, while herding do not affect portfolio construction and performance satisfaction level. A summary of the results is given in Table 6.

The regression Eqn (2) for active private investors becomes:

$$PCP = 1.246 + 0.079(RE) + 0.024(AN) + 0.185(AV) + 0.121(GA) + 0.323(OV) + \varepsilon$$

Hypothesis	Statement	Decision
H1	Heuristic variables significantly influence portfolio construction and performance satisfaction level	*Accepted*
H2	Herding variables significantly influence portfolio construction and performance satisfaction level	Rejected

Table 6. Summary of hypothesis testing (private investors)

The results (Table 7) show that overconfidence bias has a significant influence on the investment decision-making of an investor as its significance value is less than 0.05. The remaining biases, i.e. representativeness, anchoring, availability and gamble's fallacy have significance value higher than 0.05, indicating that they do not have any influence on portfolio construction and performance satisfaction level. This result is supported by the study of Lai *et al.* (2013), who found that retail investors are overconfident during bull and bear markets. Moreover, the above result is in line with Lewis (2018) study, who demonstrated that overconfidence is very important for investors' long-term financial well-being. Our result is conflicted with the study of Fachrudin *et al.* (2017), who showed that there is no effect of overconfidence on investment decision. Lastly, Im and Oh (2016) showed that overconfidence is related to poor performance in contrast with our result.

4.2 Robustness test of private investors results

We conducted a robustness test of the above results on a second sample containing finance professionals by analyzing how heuristics and herding affect portfolio construction and performance satisfaction level. The total target finance professionals holding professional certification C (Portfolio management) and/or certification B1 (Providing investment advice) for this study is 619 based on the list of certified persons (Greek Republic Capital Market Committee NPDD Athens, 28/07/2020). The recommended sample size of the study should be 100 finance professionals in order to be representative with a margin error of 9% a confidence level of 95%. The selected sample contained finance professionals of three private banking houses, four asset management companies, two stock brokers companies, three investment companies and a private company of receiving and transmitting asset orders in Greece.

Model Summary[b]

Model	R	R^2	Adjusted R^2	Std. error	Dubin-Watson
	0.343[a]	0.118	*0.084*	0.707	1.687

Note(s): a. Predictors: Representativeness, Anchoring, Availability, Gambler's Fallacy, Overconfidence. b. Dependent Variable: PCP / $N = 135$

ANOVA[a]

Model	Sum of sq	df	Mean sq	F	Sig
Regression	8.635	5	1.727	3.449	*0.006*[b]
Residual	64.587	129	0.501		
Total	73.221	134			

Note(s): a. Dependent Variable: PCP b. Predictors: Representativeness, Anchoring, Availability, Gambler's Fallacy, Overconfidence / N 5 135

Coefficients[a]

Model	Unstandardized coefficients B	Std. error	Beta	t	Sig
Constant	1.246	0.773		1.612	0.109
Representativeness	0.079	0.128	0.052	0.613	0.541
Anchoring	−0.024	0.112	−0.018	−0.211	0.833
Availability	0.185	0.132	0.117	1.397	0.165
Gambler's Fallacy	0.121	0.116	0.088	1.040	0.300
Overconfidence	*0.323*	0.092	0.299	3.513	*0.001*

Note(s): a. Dependent Variable: PCP / $N = 135$

Table 7.
Regression analysis for Heuristic: regression Eqn (2) for active private investors

The questionnaire (Appendix 2) for finance professionals is divided into three sections. The first section aims to elicit information about personal data (like area of activity, position held and investment services) and information about methods and techniques used for portfolio construction (like asset selection, asset allocation, methods and techniques in calculating risk, coping with exogenous events, best timing of buying assets, methods of rebalancing and evaluating performance). The rest of the sections were the same with private investors questionnaire. The finance professional's questionnaire was distributed in the same way, as private investor, through branch managers or managing directors. The total number of questionnaires returned were 97.

Based on the answers to the questionnaires, when constructing a portfolio, the finance professionals' decision about asset selection is based mainly (27.1%) on an effective and experienced management team (see Table 8). In portfolio optimization for asset allocation most finance professionals (28.9%) use sample covariance matrix or risk metrics, while, as regards, absolute risk they mostly (43.4%) use average risk, like volatility, variance or standard deviation. When dealing with an exogenous event like pandemic diseases, terrorism, etc. almost half of the respondents (45.4%) shift to asset allocation. Theme selections based on market trends is the methods that professionals' use most (34.4%), when they have to decide about market timing for buying assets. The strategy of monitoring and rebalancing their portfolios is simply using index investing or regular rebalancing (31.4%). Lastly, most of finance professionals (25%) use excess return relative to benchmark in evaluating their portfolios.

A multiple regression analysis was conducting to identify whether heuristic and herding biases influence portfolio construction and performance satisfaction level of finance professionals. The significant value of 0.001 (see Table 9) shows that our research model is significant. The adjusted R^2 is 11.2%, which means that the two independent variables only contribute about 11.2% to portfolio construction and performance satisfaction level, while other factors not studied in this research contribute 88.6%.

The regression Eqn (1) for finance professionals becomes:

$$PCP = 3.450 \ + 0.348(H) - 0.261(HER) \ + \varepsilon$$

Based on the regression equation, taking the above biases at zero, the portfolio construction and performance satisfaction level would be 3.450. The beta value of heuristic bias is 0.348, which means that 1 unit change in heuristic impacts 0.348 units change in the portfolio construction and performance satisfaction level. This means that when heuristic is shown by a finance professional, the portfolio construction and performance satisfaction level also increase, showing positive relationship between the two variables. The t value of the variable is 2.656, which is significant. The significance value is 0.009, which means that heuristic variable has a significant positive impact on portfolio construction and performance satisfaction level. In line with our finding, Oehler *et al.* (2008) come up with supported evidence of heuristic bias (home bias) in mutual fund composition. Broihanne *et al.* (2014) and Kiymaz *et al.* (2016) found that finance sector professionals are positively influenced by heuristics (overconfidence). In addition, Pikulina *et al.* (2017) tested 114 finance professionals and found that heuristic (strong overconfidence) results in excess investment, while moderate overconfidence leads to accurate investment. In contrast with our result, where individual investors and finance professionals follow heuristic bias, Menkhoff *et al.* (2013) found differences in heuristics among three investors groups (individual investors, institutional investors and investment advisors).

The beta value of the second variable (herding) is −0.261, which means that 1 unit change in herding decreases 0.261 change in portfolio construction and performance satisfaction level. As a result, if finance professional presents herding bias, portfolio construction and

In portfolio construction, your asset selection is based on	Strong and improving metrics (ROE, dividend yield, cash flow, etc.)	*22.1%*
	Effective and experienced management team	*27.1%*
	Consistent earnings growth	13.4%
	Quantitative analysis (financial forecast and valuation models)	19.1%
	Analysis of manager's alpha	13.7%
	Other	4.6%
In portfolio optimization, your asset allocation is based on	Sample covariance matrix or Risk Metrics	*28.8%*
	Explicit factor, such as CAPM	19.7%
	Factor analysis or PCA (Principal Component Analysis) predictive models	16.7%
	Shrinkage estimation (effect of R^2 shrinkage)	3.0%
	Black-Litterman approach	9.1%
	Other	22.7%
When implementing portfolio optimization, are objectives set for absolute risk?	No	7.6%
	Yes, average risk, like volatility, variance or standard deviation	*43.4%*
	Yes, tail risk, like VaR or CVaR	21.4%
	Yes, Maximum drawdown	26.2%
	Yes, other	1.4%
How do you deal with exogenous events (like pandemic diseases, terrorism, etc.)?	No action	7.1%
	Shift to asset allocation	*45.4%*
	Follow hedging strategies	28.4%
	Using stress tests, forecasting models or covariance metrics	15.6%
	Other	3.5%
Which methods do you use in order to decide the best timing for buying assets?	None	1.6%
	Flows and momentum analysis	22.6%
	Theme selections based on market trends	*34.4%*
	Economic cycles	33.9%
	Other	7.5%
What are your strategies for monitoring and rebalancing your portfolios?	None	2.5%
	Calendar rebalancing	15.7%
	Simply using index investing or regular rebalancing	*31.4%*
	Constant mix strategy with corridors	25.6%
	Other	24.8%
How do you evaluate portfolio performance?	Sharpe ratio	22.9%
	Treynor ratio	3.8%
	Sortino ratio	3.8%
	Absolute return	21.6%
	Excess return relative to benchmark	*25.0%*
	Jensen's alpha	5.1%
	Information ratio	7.2%
	Measures based on VaR	7.2%
	Other	3.4%

Note(s): * Each respondent could choose more than one answer

Table 8.
Variables affecting portfolio construction and performance (Finance professionals survey responses*)

performance satisfaction level is affected negatively. The significance value is 0.001, which means that herding has a statistically significant low-negative impact on portfolio construction and performance satisfaction level. This is supported by the study of Mobarek *et al.* (2014), who examined herding behavior in European indices and Demirer *et al.* (2014), who found significant evidence of herding behavior in the ADRs market. Moreover, Cuthbertson *et al.* (2016) found mutual fund managers to display home bias, herding, Model summary

Model	R	R^2	Adjusted R^2	Std. error	Dubin-Watson
	0.361[a]	0.131	*0.112*	0.408	2.097

Note(s): a. Predictors: Heuristic, Herding b. Dependent Variable: PCP / N = 97

ANOVA[a]

Model	Sum of sq	df	Mean sq	F	Sig
Regression	2.354	2	1.177	7.054	*0.001*[b]
Residual	15.683	94	0.167		
Total	18.037	96			

Note(s): a. Dependent Variable: PCP b. Predictors: Heuristic, Herding / N = 97

Coefficients[a]

Model	Unstandardized coefficients B	Std. error	Beta	t	Sig
Constant	3.450	0.418		8.263	0.000
Heuristic	*0.348*	0.131	0.269	2.656	*0.009*
Herding	*−0.261*	0.078	−0.339	−3.350	*0.001*

Note(s): a. Dependent Variable: PCP / N = 97

Table 9. Regression analysis: regression Eqn (1) for finance professionals

disposition effect and overconfidence. Lastly, Guneya *et al.* (2017) found herding only on a small number of occasions in US and South African markets.

The empirical results of our study on finance professionals imply that heuristic and herding contribute statistically significant to portfolio construction and performance satisfaction level.

5. Final conclusions

Designing a systematic portfolio of investment is a complex task not only for an investor but also for a finance professional. Investors should consider some basic portfolio factors when constructing their portfolio and should clearly understand the behavioral biases affecting an investment decision. Finance professionals on the other hand should overcome their behavioral biases in order to design optimal portfolios. Studies in the behavioral finance literature show that individuals do not behave rationally. However, these studies are mainly referred to different groups by studying some bias at a time and mainly focus on developed countries. In this study, we concentrate on data from Greece, a country with rapid market fluctuations over the last decade due to its deep debt-crisis followed by a promising economic growth. No studies have been carried out in Greece regarding portfolio construction and behavioral biases and thus, studying in unsearched area would be a great empirical contribution to the existing literature.

We analyze how heuristics and herding factors affect active private investors' portfolio construction and performance satisfaction level. In addition, we conduct a robustness test on the results of private investors by analyzing how heuristics and herding affect finance professionals' portfolio construction and performance satisfaction level.

The findings show that heuristic bias has a positive significant impact on private investors' portfolio construction and performance satisfaction level. The results further demonstrate that overconfidence from heuristic variables has a significant impact on private investors' portfolio construction and performance satisfaction level. The robustness test shows that heuristic again is a basic predictor of portfolio construction and performance satisfaction level. In addition, herding bias affects negatively and statistically significant finance professionals' portfolio construction and performance satisfaction level. Decision-making guided by herding can result in an environment where asset correlations are high, leading to distortions in returns and anomalies that contradict the efficient market hypothesis.

Overall, our findings for Greece are in line with empirical evidence documented in the similar studies of the existing literature. Our study helps private investors to be aware of the impact of their own behavioral biases on their portfolio construction, thus increasing the rationality of investment choices leading to market efficiency. We consider investment portfolio selection and diversification decisions and understand errors that investors made in managing their portfolios, especially, under the pressure of high volatility that Greece went through over the last decade. The results of this study help finance professionals to identify the different types of their own behavioral biases and their possible impact on optimal portfolios. Practically, under the scenario of uncertainty, it becomes necessary to design the portfolio as per the requirement of the investors. The findings are recommended to regulatory authorities in securing financial strength and making policies to avoid these biases.

Despite the valuable findings of this study, there are also limitations to be acknowledged. This paper did not address the link between biases and investor characteristics as age, gender, background, experience, etc. The study examined a good sample size, which could have been expanded further but it did not, due to COVID-19, which slowed down the process of questionnaire collection. In addition, the dramatic economic effect of the spread of coronavirus might have influenced not only the behavior of individual investors but also their answers to the questionnaires regarding the effectiveness of asset allocation, the sentiment of markets, the concepts of risk, uncertainty, herding and heuristic effects. COVID-19 pandemic has been a particularly stressful experience combining significant financial uncertainty that hampers decision-making and the ability to invest rationally. Finally, further research should demonstrate differences between individual investors and practitioners and expand knowledge about psychological influences on investment decisions by studying other biases that are not included in the present study.

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Appendix 1

Dimensions	Variable	Definition
Heuristic factor Tendency to pay attention to pieces of information that are easier to get or understand	*Representativeness*	The level of how well or how accurately something reflects upon a sample
	Anchoring	Imagine any initial value, i.e. anchor and solutions tailored to it
	Availability	The fact that something can be bought, used or reached or the state of being available
	Gambler's fallacy	The incorrect belief in the negative autocorrelation of non-auto-correlated random sequences
	Overconfidence	A tendency to hold a false and misleading assessment of personal skills, intellect or talent. The false assumption that someone is better than others
Herding factor Tendency to follow actions of others	*Impact of others buying and selling*	Imitating the observed actions of others on buying and selling asset instead of following own beliefs and information
	Impact of others asset allocation	Imitating and follow others investors asset allocation instead of following own beliefs and information
	Impact of others investment outlooks	Imitating and track other investors' investment outlooks and apply in to own investment decisions
	Impact of following information from reliable media	Imitating and use information from reliable economic media and Internet sites in making investment decisions instead of following own beliefs and information
Investment performance		The level of satisfaction of investor's portfolio construction and performance

***Source(s)**: Pompian (2011). Behavioral Finance and Wealth Management: How to Build Optimal Portfolios That Account for Investor Biases. John Wiley & Sons, p. 51,62,75,94

Table A1. Definitions* of variables

Appendix 2

Supplementary data

Supplementary material related to this study can be found on-line at: https://drive.google.com/drive/folders/1D9QyxIBuDBCXYe3Wbfm-qSg3dptvO4Hh?usp=sharing.

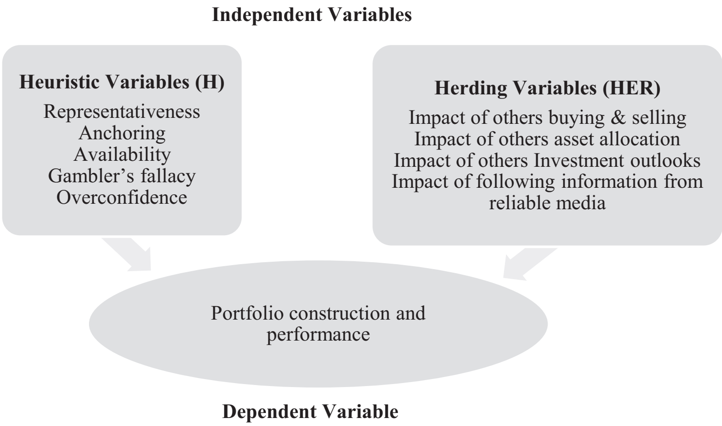

Figure A1.
Model factors

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