Heliyon 7 (2021) e06495

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Impact of education, age and gender on investor's sentiment: A survey of practitioners9

Manuel Gonzalez-Igual [a,*], Teresa Corzo Santamaria [b], Antonio Rua Vieites [b]

[a] Universidad Pontificia Comillas ICADE, Madrid, Spain
[b] Faculty of Economics and Business Administration, Universidad Pontificia Comillas ICADE, Madrid, Spain

ARTICLE INFO

Keywords:
Behavioral finance
Investor survey
Sentiment
Education
Age
Gender

ABSTRACT

The field of behavioral finance lacks a homogeneous and structured theoretical framework. The purpose of this paper is to contribute to further systematization in the field by analyzing the impacts of education, gender and age on investor behavior and sentiment.

The study is based on online anonymous surveys given to 106 professional investors active in the Spanish market during February 2017. The survey includes control questions, seven questions regarding investors' sentiment to elaborate a confidence index and twenty questions concerning the practitioner's view of behavioral finance.

We first identify a gap between the relevance of behavioral finance and the lack of education in the field. We also find a clear misalignment between the investors and their clients' profiles related to their level of confidence. In that regard, the use of the institutional investor confidence index mitigates self-perception bias and is a key element in determining investors' real profiles.

Consistent with prior research, we find that female investors view themselves as more driven by rational analysis and are more risk averse while younger investors are more influenced by cognitive and emotional biases. As a key contribution, we establish a model to determine investors' sentiment, which shows that female and more experienced practitioners exhibit higher levels of optimism and confidence.

1. Introduction

Three main premises, which entail the lack of arbitrage opportunities, characterize classical finance: 1) investors are rational agents (Miller and Modigliani, 1961), 2) financial markets are efficient in processing information (Fama, 1965, 1970), and 3) expected returns are a function of risk (Markowitz, 1952; Sharpe, 1964). As described by Thaler (1999), investors are considered to be rational in two ways: 1) making decisions according to expected utility theory and 2) making unbiased forecasts about the future.

Conversely, in real life, every investor has limited access to information, is surrounded by external constraints and is influenced by its own personal behavior. There is ample evidence that investors are not rational agents and that biased beliefs and unconventional preferences lead to suboptimal investment decisions (Barberis and Thaler, 2005). Because of investors' cognitive, emotional and social biases, markets exhibit several financial anomalies, such as the equity premium puzzle (Mehra and Prescott, 1985), the momentum effect (Jegadeesh and Titman, 1993) or violations of the law of one price (Lamont and Thaler, 2003).

In the twenty-first century, the dotcom bubble, the subprime mortgage crisis and the recent Bitcoin bubble are prime examples of irrational behavior, described by Shiller (2000, 2006) as "irrational exuberance". Evidence of investors' under- and overreaction has led to the development of behavioral finance, which seeks to understand the impact of investors' limited rationality on asset pricing and on the functioning of financial markets. Behavioral finance represents a new paradigm in the field of finance with three Nobel prizes awarded over the last 20 years: Daniel Kahneman in 2002, Robert J. Shiller in 2013 and Richard H. Thaler in 2017.

However, despite the multiple identified financial anomalies and the development of flagship psychological theories, the field of behavioral finance lacks a homogeneous and structured theoretical framework (De Bondt et al., 2009). In addition, despite the relevance given by practitioners to behavioral finance, professional investors recognize that their level of training is clearly insufficient.

* Corresponding author.
E-mail address: manuel.gonzalez@avangrid.com (M. Gonzalez-Igual).

https://doi.org/10.1016/j.heliyon.2021.e06495
Received 5 January 2020; Received in revised form 29 November 2020; Accepted 9 March 2021

The aim of this paper is to contribute to further systematization in the field by analyzing the impacts of education, age and gender on investors' behavior and sentiment based on direct anonymous surveys given to 106 professional investors active in the Spanish market, 51% of which are CFA (Chartered Financial Analyst) Charterholders. Our study analyzes the alignment between investors and their clients' behavioral profiles and how this may be impacted by education, age and gender.

Sentiment studies not only provide relevant insights concerning investors' biases associated with stock market forecasts, but also display predictive ability for stocks returns (Fisher and Statman, 2000). Two keystone papers are Baker and Wurgler (2006, 2007) whose innovative approach to examining the relation between sentiment and asset prices led to a renewed focus on investor sentiment.

Understanding how investor psychology affects asset prices is critical to explaining the functioning of financial markets. Our analysis sheds light on the diverse results obtained so far in the literature and identifies the key behavioral biases and factors impacting investors' sentiment.

This study contributes to the literature and to the investment community in five ways. First, regarding education, we find a clear gap between the importance of behavioral finance for the practitioner and the lack of learning experience in the field.

Second, concerning gender and consistent with existing literature our research shows that female investors view themselves as more driven by rational analysis and are more risk-averse.

Third, regarding age, despite their lack of experience and education in the field, young investors unanimously recognize the relevance of behavioral finance and acknowledge being more influenced by cognitive and emotional biases.

Fourth, we analyze the different types of behavioral investor's profiles as defined by the Bailard, Biehl and Kaiser (BB&K) model (1986) and find a clear misalignment between investors and their clients related to their level of confidence.

Our final contribution is to establish a model for investors' sentiment based on the confidence index as defined by Robert Shiller (2000). We analyze the impact of our three independent variables (Education, Age and Gender) and find that women and more experienced investors have a higher level of confidence among practitioners, while education does not have a significant impact on sentiment.

The remainder of this paper is organized as follows. In the second section, we provide a literature review. In the third section, we develop the methodology of our experimental analysis and discuss the potential limitations of the survey. In the fourth section, we discuss the results and implications of our study. We conclude in the fifth section. All the questions and responses to the survey are included in the Appendix.

2. Related literature

2.1. Prevailing behavioral biases: overconfidence, loss aversion and herding

According to the theoretical framework of behavioral finance, investors exhibit irrational financial decision making because they are not capable of processing available information rationally due to cognitive and emotional biases. The two main psychological theories are the representativeness heuristic (Tversky and Kahneman, 1974) and prospect theory (Kahneman and Tversky. 1979).

As stated by prospect theory, investors tend to evaluate bets in terms of losses and gains instead of expected final wealth because of the influence of loss aversion bias (Kahneman and Tversky, 1979). They are approximately twice as sensitive to losses as they are to gains (Schneider and Lappen, 2000). Mental accounting bias (Thaler, 1985) is closely related to loss aversion as investors tend to categorize their investments on different levels (Grinblatt and Han, 2005) in terms of potential losses and gains but ignore the interaction among those investments.

Moreover, according to the representativeness heuristic, investors are overconfident as they overestimate their knowledge and ability to predict future outcomes. They tend to consider a certain event as typical or representative (Tversky and Kahneman, 1974); and therefore, they do not properly apply the laws of probability, paying too much attention to the strength of the evidence and not enough to the statistical weight. Utilizing a data set of 78,000 investors, Barber and Odean (2000) found that overconfident behavior results in excessive trading, which negatively affects portfolio managers' performance. Evidence of the overconfidence of institutional investors is less available than that for individual investors since finding a suitable sample is more difficult. Chuang and Susmel (2011) find that individual investors are more prone to overconfident trading behavior than institutional investors. Overconfidence is present in both groups, but the bias is stronger in the sample of less sophisticated investors (Chen et al., 2007).

Contrary to the phenomenon of overconfidence, conservatism advocates that investors are subject to status quo bias (Edwards, 1968; Samuelson and Zeckhauser, 1988) as they generally prefer to avoid changes in their investment decisions and do not properly adapt in response to new information. Similarly, they are subject to confirmation bias, considering only the positive evidence related to their investments.

Herding or social interaction also plays a key role in investor behavior. According to Lakonishok et al. (1992), herding behavior appears when the proportion of investors trading a particular stock is disproportionately higher than the expected proportion trading across all stocks. Prechter (2001) found evidence for this phenomenon of imitation in large groups of financial professionals whose activity responds to signals from the behavior of others. Ortiz, Sarto and Vicente (2013) find evidence of herding behavior among fund managers on a country level, while Menkhoff and Nikiforow (2009) find that herding is the most relevant bias according to fund managers. Fenzl and Pelzmann (2012) provide a comprehensive review of the impact of social conditioning on financial markets as a key element to understand the boom and crash cycles in financial markets such as bubbles (Shiller, 2000, 2006) or momentum. As stated by the authors, "collective behavior does not simply sum up pre-existing individual motives and preferences". Hence, herding would have the effect of amplifying the impact of other significant investor biases such as overconfidence or loss aversion. However, herding should not necessarily be considered irrational behavior since some investors may have better information or better skills than others and therefore are likely to be followed by their peers (De Bondt, Mayoral and Vallelado, 2013).

Hirshleifer (2015) highlights the social dimension of investor irrational behavior and the need to move from behavioral finance to social finance by analyzing the structure of social interactions and how these affect financial outcomes.

In brief, the decision-making process is conditioned by several conflicting biases, such as overconfidence, loss aversion, or herding, among others, that tend to persist over time. The main goal of our research is to determine the impacts of education, age and gender on the referred investor's behavioral biases.

2.2. Impacts of education, age and gender on investors' behavior

Existing literature shows that behavioral biases are closely related to the individual's underlying biological characteristics, education background and experience. The recent paper by Metawa et al. (2018) also studies the effects of age, gender and education as well as investor sentiment, on investment decisions. However, we differ in that our paper focuses on the behavior of institutional investors.

Financial literacy becomes key when investing. Muralidhar (2019) raises this issue and links it to financial innovation, and Hibbert et al. (2012) find that finance professors are less prone to behavioral biases, thus confirming the importance of financial literacy when investing.

Even if slowly, behavioral finance is beginning to be included in university curriculums and textbooks. Behavioral finance is also part of professional education, such as the Chartered Financial Analyst (CFA) curriculum.[1] Shukla and Singh (1994) develop an early study on the impact of being a CFA versus non-CFA Charterholder fund manager.

Institutional investors are becoming increasingly educated about behavioral finance and the inefficiencies that behavioral biases can create in the financial markets. Behavioral biases affect institutional investors through the underlying investor base. An institutional manager needs to be aware of the implications of each relevant behavioral bias. Pompian (2012) develops a model of individual behavior to help fund managers understand the wide range of clients and how to best serve their individual needs. Some studies of mutual funds note that investors hiring advisors must obtain some benefits apart from portfolio returns (Hortacsu and Syverson, 2004). Gennaioli et al. (2015) and Olsen (2012) study the fiduciary role of investors and financial advisors providing "peace of mind" to their clients, while Olson and Riepe (2010) note that investors who utilize behavioral finance are more likely to receive the agreement and understanding of their clients. Our study analyzes the alignment between investors and their clients' behavioral profiles and how this may be impacted by education, age and gender.

Aging causes a well-documented decline in people's cognitive abilities, which empirically dominates any experience effect. According to Korniotis and Kumar (2011), older investors exhibit worse investment skills even though they are more experienced. In fact, financial mistakes appear to follow a U-shaped pattern with the fewest mistakes occurring at approximately age 53 (Agarwal et al., 2009). Although aging decreases cognition and financial literacy, it is not associated with a decrease in confidence in managing one's own finances (Gamble et al., 2014). Individuals appear to overweight their personal experience in the stock market with insufficient consideration of all available data (Greenwood and Shleifer, 2014). This finding would be aligned with the representativeness heuristic (Tversky and Kahneman, 1974) but from an age perspective. Conversely, Lin et al. (2010) find that younger and male traders tend to prefer online trading, which in turn is associated with more active trading and, hence, with overconfident behavior.

An extended stream of the literature compares trading choices between male and female professional money managers. On the one hand, according to Lundberg et al. (1994), men are generally more overconfident than women, especially in masculine domains, such as the financial industry. Based on an experiment involving over 1,300 individuals, Estes and Hosseini (1988) find evidence that women are less confident in investment decisions than men. Barber and Odean (2001) also find significant gender differences in overconfidence, indicating that men trade 45% more actively than women do; and therefore, male investors reduce their net annual returns through trading by almost one percentage point. Concerning the impact of gender on risk aversion, Powell and Ansic (1997) find that women are less risk-seeking than men. Similarly, according to Olsen and Cox (2001), female investors consider risk attributes to a greater extent than men, especially as it relates to the risk of losses and uncertainty. Similarly, Li et al. (2013) find that female sell-side analysts tend to be more risk-averse in their recommendations. Pompian and Longo (2004) also find differences related to gender: while women tend to be realistic and pessimistic and have low risk tolerance, men tend to be overconfident and unrealistic and have high risk tolerance.

There is an additional prolific line of study related to gender, associated with experiments on steroids. Overall, the results show that there are significant individual and joint effects of steroids on investment biases. The results show that testosterone and cortisol are related to higher portfolio turnover and impact financial choices (Nofsinger et al, 2018, 2020; Ahmed et al., 2019).

On the other hand, several other studies have investigated differences between male and female professional money managers and overall find no significant gender differences among professional investors (Atkinson et al., 2003). Bliss and Potter (2002) find that female fund managers hold portfolios with marginally more risk than men, but they find no significant difference in performance and turnover between the two groups. Beckmann and Menkhoff (2008) analyze the survey responses of 649 fund managers and confirm that female fund managers tend to be more risk averse, as predicted by gender studies. However, the expected lower degree of overconfidence by women is insignificant in fund management. Durand et al. (2019) study myopic loss aversion and find that, when accounting for subjects' personality traits, gender does not have a robust association with this behavioral bias.

2.3. Modeling investor's profiles: BB&K Five-Way Model

To examine investor types and personalities and to evaluate the impact of our three independent variables, we use the BB&K Five-Way Model. This model, developed by Bailard et al. (1986), classifies investor personalities into five different groups based on their level of confidence and risk aversion. The level of confidence is reflected in the emotional choices made based on how much an investor may worry about a certain course of action or decision. Investors may range from confident to anxious. Method of action is reflected in how methodical an investor is, as well as how analytical and intuitive they are. This can range from careful to impetuous. The five investor personality profiles are the adventurer, the celebrity, the individualist, the guardian and the straight arrow.

Some compelling studies applying this model are the papers by Thomas and Rajendran (2012) which constitutes an application of this model to the Indian market, as well as Akhtar et al. (2014). NazariPour et al. (2020) applies the model to the Tehran Stock Exchange.

For the visual representation of this model, two axes of individual psychology define four quadrants, as shown in Figure 1.

The axis named "confident-anxious" reflects the emotional choices made. The other axis, named "careful-impetuous," reflects how methodical and risk-averse an investor is. Each profile is in a different quadrant except for the straight arrow profile, which is situated at the intersection of both axes.

The first quadrant constitutes the adventurer's profile, characterized as being highly confident, risk-loving and emotionally biased. In addition, adventurers are difficult to advise since they have their own strong ideas about investing. Similarly, the individualist investor has personal ideas about investing and has a high degree of self-confidence but a higher level of risk aversion. Additionally, the individualist is predominantly influenced by cognitive biases.

People who do not have their own ideas about investing and are afraid of being left out are denoted as celebrities and form the second quadrant. They are mainly driven by cognitive biases. Finally, guardian investors are more careful than individualists and are not particularly

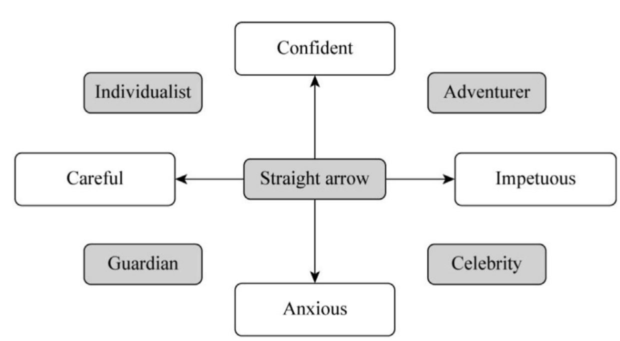

Figure 1. BBK Model (Bailard et al., 1986). This figure represents the five different investor personality profiles as defined per the BB&K Five-Way Model, based on the level of confidence and risk aversion.

[1] The CFA program is one of the highest distinctions in the investment management profession (see https://www.cfainstitute.org/en/programs/cfa).

interested in excitement. They are dominated by emotional rather than cognitive biases.

In short, the two main characteristics that define investors' behavioral profiles are confidence and risk exposure. To be able to compare the investor's own perception with a more objective reference, we introduce the stock market confidence index, explained in detail in the following section.

2.4. Measuring investors' sentiment: institutional investor confidence index

The literature concerning investor sentiment is vast, and we find controversy about how to measure investment sentiment[2]. Since investor sentiment is considered to be a set of non-revealed information, validating investors' sentiment as a relevant variable in financial markets, becomes a substantial challenge to researchers. As there are no direct measures of investors' sentiment, studies should rely on indirect proxies.

A noteworthy and very fruitful line of study concentrates efforts developing new proxies based on the massive information available nowadays through social media using new technological advances that enable text analysis (Tetlock 2007; Da et al., 2011; Leitch and Sherif, 2017; Yadav and Vishwakarma 2020, or Wang et al., 2020)[3], often testing these measures against the stock exchange performance. In this text analysis framework, natural language processing techniques (NLP) have become key to capture sentiments and semantics in a more accurate and nuanced way (see, i.e., Xing et al., 2018; Xing et al., 2020). Given that investor sentiment is such an ambiguous and still imprecise topic, NLP applications can be used to obtain insights, make inferences and create additional methodologies and artefacts to advance knowledge.

Very recent studies include the paper on international sentiment measure by Weißofner and Wessels (2020), and the paper by Nogueira and Pinho (2020) which, in addition to presenting an extensive literature review, develop a set of investors' sentiment proxies. All these outstanding efforts confirm the relevance of this variable which best proxy continues to be an open issue.

Direct investor sentiment measures are derived from surveys directly asking individuals how they feel about current or future economic and stock market conditions while indirect ones represent economic and financial variables susceptible to capture investors' state of mind.

In our research, we replicate, using Spanish data, the stock market confidence indexes, which measures investor sentiment through direct survey data, developed by the Yale School of Management, under the direction of Robert Shiller (2000).[4]

Based on this, we introduced five questions in the survey to measure investor confidence. With the responses, we established the Institutional Investor Confidence Index (IICI), composed of these five different indices related to investors' expectations for the Spanish stock market: i) the perspectives' index, ii) the valuation index, iii) the short-term recovery index, iv) the long-term recovery index, and v) the crash risk index. To also consider macro expectations, we include two additional indices related to the expected evolution of interest rates (IICI 2): vi) the short-term interest rate index and vii) the long-term interest rate index.

Once these indices are determined, we average the results to obtain the IICI and IICI 2. The result of the index can range from -100 to 100. A negative index indicates a pessimistic perspective of the market whereas a positive index denotes an optimistic outlook.

The referred confidence index primarily assesses the degree of stock market optimism (or pessimism) of the survey participants and not just their degree of overconfidence. Overconfidence is characterized by an individual's belief that the precision of their forecasts is greater than it should be, and therefore overconfidence is associated with narrow confidence intervals (Glaser and Weber, 2010). However, according to psychological studies (Weinstein, 1980) and specific finance research (Mishra and Metilda, 2015), the two concepts are closely related as overconfidence can also be associated with "unrealistic optimism". In his survey of behavioral finance, Hirshleifer (2015) also directly links overconfidence and overoptimism, highlighting that people tend to be overoptimistic, which affects their economic and financial decisions.

2.5. Main hypotheses for our research

Based on our literature review and our knowledge in the field we established the following five hypotheses for our research:

- H1: There is a gap between the importance of behavioral finance for investors and their level of education in the field.
- H2: There are significant gender differences impacting investor sentiment. Female investors tend to be more driven by rational analysis and are more risk-averse.
- H3: There are significant age differences impacting investor sentiment. More senior investors tend to overweight their personal experience and usually have higher level of confidence.
- H4: There is a misalignment between investors and their clients related to their behavioral profile.
- H5: Higher education in behavioral finance does not reduce investors' irrational behavior.

3. Data and methodology

3.1. Data from the survey

This study is based on an anonymous survey given to professional investors active in the Spanish market during February 2017. This data set is based on online surveys given to fund managers associated with the Funds People monthly publication and who are members of the CFA Society Spain.

The survey was composed of six control questions, seven questions regarding investors' sentiment to calculate the confidence index and twenty questions concerning the practitioner's view of behavioral finance. The Appendix includes all the questions included in the survey.

Our survey was completed by a total of 106 professional investors, 85% of which directly work in the financial industry. Approximately 60% of the practitioners are investment advisors, fund managers or work in investment analysis; and the remaining 40% work in investment banking, private equity or in other financial positions.

Regarding the main independent variables of our study (education, gender and age), 51% of the participants are CFA Charterholders (54 investors), 26% are women (28 investors) and 56% are less than 40 years old (59 investors). The size of the sample and subsamples are considered large enough to provide statistically significant conclusions.

3.2. Potential biases and limitations of the survey

Self-reported surveys are to be treated with a certain degree of suspicion since participants may have erroneous views of themselves. This self-perception bias is due to the potential gap between the answers

[2] In this paper we follow Brown and Cliff (2005) and understand that sentiment represents the expectations of market participants relative to a norm: a bullish (bearish) investor expects returns to be above (below) average, whatever "average'' may be.

[3] There is a significant amount of papers recently published on different types of sentiment, given the social networks data availability and the technology developed. However, our paper is based on investor sentiment at the cross road with behavioral biases, not focusing on other uses of investor sentiment or on general sentiment, for this reason we do not elaborate further this vast literature.

[4] Regular questionnaire investor sentiment surveys have been done continuously since 1989. These indexes have a span of nearly thirty years, and thus are the longest-running effort to measure investor confidence and related investor sentiment. Similar surveys have been conducted in the Chinese and Japanese markets.

provided by the respondents and their real thoughts and actions (Baker and Wurgler, 2006). The anonymous character of our survey can help to mitigate this impact. Additionally, measuring the actual investor sentiment through the institutional investor confidence index is a key element to determine the investors' real profiles and to establish a comparison with their own perceptions.

An additional element of potential distortion in our surveys is the self-selection bias. This arises when individuals select themselves into a group, potentially causing nonprobability sampling. Investment professionals have generally limited available time, which might further influence this bias. In our case, the respondents may have decided to participate based on their interest in behavioral finance. Therefore, participants may exhibit a higher than average level of education or interest in behavioral finance.

In addition, our sample consists of 28 women versus 78 men, which may entail a small sample bias in the gender analysis. Our statistical analysis considers the sample size when determining the level of significance of our conclusions. Furthermore, there may also be self-selection bias in the sense that these women may have entered the finance industry because they are better educated and more confident. However, this is probably reflective of the reality of the financial industry. According to Oliver Wyman's Women in Financial Services 2020 Report, women constitute only 20% of the average company's workforce at the executive level and only 35% at the professional level and above. Our female sample representation (26%) reflects this reality.

Finally, the geographic scope of our survey, administered to institutional investors in Spain, also compels us to be cautious in drawing general conclusions for the investment community. The fact that 51% of our participants are CFA Charterholders, a globally recognized certification, provides a certain degree of homogeneity and helps draw general conclusions. The 54 CFA Charterholders participating in our survey represent close to 10% of the CFA population in Spain (as of February 2017), which is considered representative for this subgroup of interest. However, considering the impact of cultural factors on human behavior, future research will include extending our survey to other geographical areas.

3.3. Methodology and theoretical basis for statistical analysis

We focused our analysis on the impact of education, gender and age on i) the level of awareness and knowledge in the field, ii) prevailing cognitive and emotional behavioral biases; and iii) investors' profiles and alignment with their clients.

We discretized all our variables, and we empirically contrasted our findings through different statistical tests, fulfilling the required conditions (normality, equality of variances and a large data sample). The tests that we performed are both parametric and nonparametric:

- **Parametric tests**: The student's t-test (H0: $\mu 1 = \mu 2$) or ANOVA (H0:$\mu 1 = \cdots = \mu i = \cdots = \mu k$) are used to test the equality of means for two or more groups.
- **Nonparametric tests**: The binomial test (H0: homogenous binomial distribution ($p = 0.5$)), χ^2, gamma (γ) and/or Cramer's V are used to test the association between variables (H0: there is no association between variables). Particularly, the gamma test ($-1 \leq \gamma \leq 1$) constitutes another measure of association between variables (positive if $\gamma > 0$ or negative if $\gamma < 0$) when variables are ordinal, dichotomous or a mixture of both. Cramer's V test is used when the variables are nominal ($0 \leq V \leq 1$).

For ordinal variables or when the required conditions are not fulfilled, we use the Mann-Whitney test for two groups or the Kruskal-Wallis test if there are more than two groups.

Finally, to build a model to determine investors' sentiment, we generate a factorial confidence index based on factorial analysis, reducing investor sentiment to a single variable that is a linear combination of the five subindices that define the IICI. Using this new index as the dependent variable, we develop a multiple linear regression model for the confidence index based, among others, on our three main independent variables.

4. Results and discussion

4.1. Awareness and education in behavioral finance

We start by analyzing the level of awareness and education in the field (questions 6, 7, 8, 17 and 18 in the Appendix). A clear majority of practitioners (92%) recognize the relevance of behavioral finance to making investment decisions. According to the nonparametric binomial test, the relevance of behavioral finance for professional investors is statistically significant (p-value = 0.00).

Despite this, 48% of investors have less than ten hours of education in behavioral finance, and 20% have no training at all, which compels us to be cautious with the findings from our study. However, considering the professional background of the respondents and their academic background (51% are CFA Charterholders), we can assume that their general financial knowledge is adequate and that the lack of training is specific to the field of behavioral finance and reflective of the reality in the industry.

Surprisingly, we found no relation between the level of training in behavioral finance and the relevance assigned to the area ($\chi^2 = 0.180$, p-value = 0.91; $\gamma = 0.077$, p-value = 0.80). Ninety-two percent of investors with 10 h or less of training consider it relevant versus 93% with more than 10 h of training.

When asked about the adequacy of the education they received in finance, 73% of practitioners consider it to be inappropriate, and 57% of those stated that the main reason is the lack of education in behavioral finance. This validates our first hypothesis (H1): there is a significant gap between the importance of behavioral finance for investors and their level of education in the field. Most investors consider that the lack of education in behavioral finance is due to the lack of structure and clarity of the theory (61%) or to its complexity (19%).

4.1.1. Impact of CFA accreditation on level of awareness and education

Regarding CFA accreditation, 100% of CFA Charterholders acknowledge the importance of the field compared to 85% among non-CFA Charterholders.

Moreover, as shown in Figure 2, CFA Charterholders have a higher level of training as only 7% stated that they had no education in behavioral finance compared with 36% for non-CFA Charterholders. In addition, 65% of CFA Charterholders have more than 10 h of training in behavioral finance compared with 38% of non-CFA Charterholders.

If we discretize the variables CFA accreditation (no accreditation = 1, other accreditation = 2, and CFA Charterholder = 3), relevance (nonrelevant = 1 and relevant = 2) and hours of learning in behavioral finance (0 h = 1, less than 10 h = 2, and more than 10 h = 3), we find a significant association between CFA accreditation and i) the relevance of the field ($\gamma = 0.93$, p-value = 0.003) and ii) the hours of education in behavioral finance ($\chi^2 = 205$, p-value = 0.006 and $\gamma = 0.44$, p-value = 0.000).

Moreover, we find a significant association between having CFA accreditation and the adequacy (question 17) attributed to education in finance ($\chi^2 = 6.86$, p-value = 0.032). In general, CFA Charterholders tend to consider finance education to be adequate.

4.1.2. Impact of age on level of awareness and education

We find a strong relation between age and level of awareness in the field: the younger the investor, the higher the relevance of behavioral finance. One hundred percent of practitioners below 40 years of age recognize the importance of behavioral finance versus 86% for investors from 40 to 50 years old and only 43% for investors older than 50 years. There is a statistically significant association between these discretized variables ($\chi^2 = 37.2$, p-value = 0.000 and $\gamma = -0.962$, p-value = 0.002).

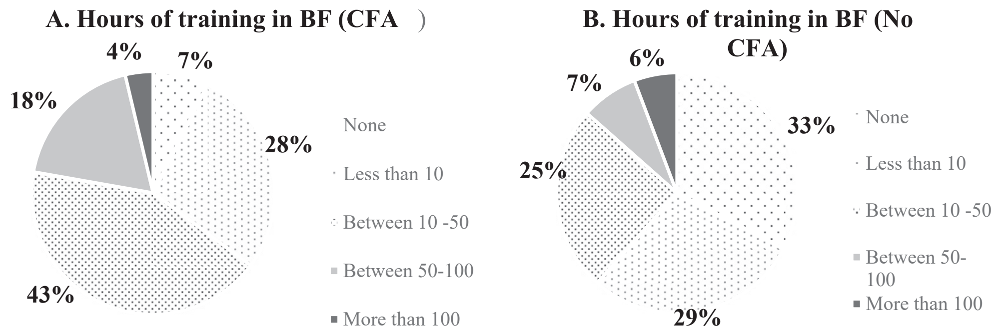

Figure 2. Education in Behavioral Finance vs. CFA Accreditation. These two pie charts represent the hours of training in Behavioral Finance for CFA and non-CFA Charterholders.

The negative sign of γ implies that the younger the investor is, the higher the relevance of behavioral finance.

However, despite their higher interest in behavioral finance, young investors do not have a higher level of training. Among investors younger than 40 years, 49% have less than 10 h of education in behavioral finance (versus 48% of total investors), and 25% have no education in the field (versus 20%). We did not find any significant statistical relation between age and the level of training ($\chi^2 = 0.708$, p-value = 0.950 and $\gamma = 0.049$, p-value = 0.761). Among non-CFA young investors, 63% have less than 10 h of training in behavioral finance (versus 65%), and 46% have none (versus 36%).

Here, again, we find a clear gap between the importance of behavioral finance for the practitioner and his lack of learning experience in the field, supporting our first hypothesis (H1). It is already twenty years after Richard Thaler (1999) predicted the "End of Behavioral Finance" as he expected it to be viewed as a redundant phrase; however, professional investors still have a clear training deficit in the field.

4.1.3. *Impact of gender on level of awareness and education*

In our survey, we find no significant relation between gender and the relevance of behavioral finance: 89% of women consider behavioral finance relevant versus 94% of men ($\chi^2 = 0.55$, p-value = 0.46). When analyzing gender for the non-CFA population, we still found no significant difference (87% of women versus 83% of men).

Regarding the level of education, we find significant differences related to gender, although at 10% of significance level, in particular, if we analyze the non-CFA Charterholders. Women have a superior level of education in the field. Fifty-two percent of women have more than 10 h of training in behavioral finance versus only 28% of men, and 45% of men have no training in behavioral finance versus 11% of women ($\chi^2 = 4.56$, p-value = 0.10). The higher level of education might be a possible explanation for the gender differences among investors as it relates to risk aversion and overconfidence.

4.2. *Impacts of education, age and gender on prevailing behavioral biases*

Asked about the main driver in their decision-making process (question 19), professional investors indicate that irrational biases (emotional, cognitive and herding) clearly prevail (65%) versus rational analysis (35%). The prevalence of irrational behavior by investors was statistically significant ($\chi^2 = 27.59$, p-value = 0.000).

According to practitioners, herding is the predominant bias (39%) compared with the other two main categories (emotional and cognitive biases) considered together (27%). This agrees with the results obtained by a survey conducted by the CFA Institute among 724 practitioners who considered herding to be the most influential bias in the investment decision-making process (CFA Institute, 2013). This is also aligned with empirical evidence from Menkhoff and Nikiforow (2009) showing that herding is the strongest bias according to fund managers. Hirshleifer (2015) highlights the relevance of social interaction to understand investor behavior and the need to move beyond behavioral finance to social finance.

As described in Figure 3, the prevalence of herding is particularly stronger for CFA Charterholders (59%) whereas rational analysis prevails (54%) for non-CFA Charterholders.

Regarding gender, men are recognized to be more biased than women. Rational analysis is considered to be the main decision-making factor for 57% of women (vs. 27% of men) whereas herding behavior is the most relevant aspect for 44% of men (vs. 25% of women). Here we find a significant difference related to the main decision-making factor and gender ($\chi^2 = 8.35$, p-value = 0.039; $\gamma = -0.431$ p-value = 0.012). The negative value of γ is associated with a stronger focus on rational analysis for female investors and supports our second hypothesis (H2).

Regarding age (younger or older than 40 years), we find that younger investors are more driven by herding behavior (44% for younger vs. 32% for older) whereas rational analysis prevails for older investors (43% for older vs. 29% for younger). If emotional and cognitive biases are considered together, we do not find a significant difference with age ($\chi^2 = 7.685$, p-value = 0.262; $\gamma = -0.25$, p-value = 0.262).

In questions 8 and 9 of our survey, investors are asked about their main cognitive and emotional biases. As shown in Figure 4, regarding cognitive biases, confirmation bias is the most widely accepted among investors (34%), followed by representativeness (26%), mental accounting (24%) and conservatism (16%), respectively. Additionally, as described in Figure 4, CFA Charterholders especially emphasize the relevance of confirmation bias, which is considered to be the most relevant bias by 42% of them (versus 25% for non-CFA Charterholders).

Regarding emotional biases, loss aversion is the most relevant one according to 57% of practitioners, which supports prospect theory (Kahneman and Tversky, 1979). We do not find significant differences concerning the relevance of loss aversion for CFA Charterholders (59%) or non-CFA Charterholders (54%) ($\chi^2 = 1.45$, p-value = 0.69; VCramer = 0.117, p-value = 0.69), for gender (predominant for 52% of women versus 55% of men; $\chi^2 = 1.76$, p-value = 0.62; VCramer = 0.129, p-value

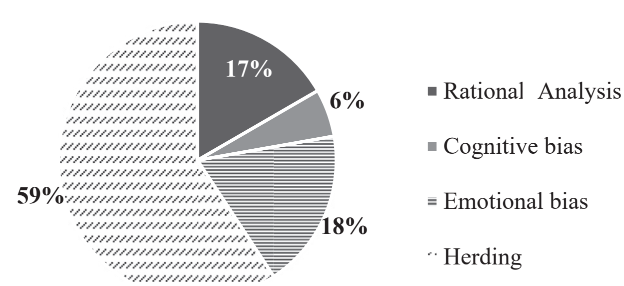

Figure 3. Most Relevant Biases for CFA Charterholders. This pie chart represents the main decision-making drivers according to CFA Charterholders participating in our survey.

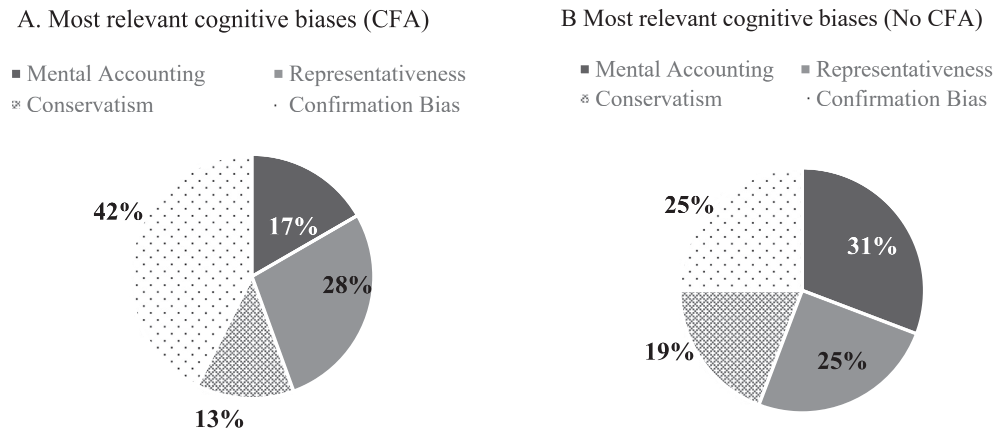

Figure 4. Most Relevant Cognitive Biases. These two pie charts represent the most relevant cognitive biases for CFA and non-CFA Charterholders.

= 0.62) or for age (χ^2 = 6.45, p-value = 0.69; VCramer = 0.144, p-value = 0.69).

4.3. Professional investors' and clients' profiles

Considering the BB&K Five-Way Model framework, two personality questions were included to determine how professional investors view themselves and how they see their clients (questions 2 and 3).

Table 1 summarizes the results related to the investors' profile. Overall, investors view themselves as being predominantly highly confident (64%) and risk-averse (61%), and their predominant profile is the individualist (42%) followed by the adventurer (23%).

We find significant differences regarding gender related to the level of risk aversion (χ^2 = 4.77, p-value = 0.029 and ɣ = -0.498, p-value = 0.018). According to their own perception, women are more risk averse (79%) than men (55%), as we can see in the following perceptual map (Figure 5). This validates our second hypothesis (H2) and implies significant gender differences related to unconventional preferences and, therefore, to emotional biases, such as loss aversion. This leads to different investment strategies depending on gender.

However, we find no significant differences in investors' confidence related to gender. Therefore, the significant difference related to the overall profile is relatively weak (χ^2 = 5.2, p-value = 0.159 and VCramer = 0.22, p-value = 0.159).

Moreover, we do not find significant differences related to having CFA accreditation (χ^2 = 0.069, p-value = 0.995) or age (χ^2 = 3.28, p-value = 0.773) and investor profiles.

Table 2 summarizes the results on how investors view their own clients:

Investors predominantly view their clients as having low confidence (73%) and high-risk aversion (83%); consequently, the predominant profile is the guardian (66%). Interestingly, the results show a clear misalignment between the professional investor and his clients, as shown in Figure 5.

The following bar chart (Figure 6) shows that the most common profiles among professional investors are the adventurer and the individualist whereas their clients are mainly viewed as guardians. Hence, practitioners view themselves as confident and risk seeking while they see their clients as risk averse and insecure. This validates our fourth hypothesis (H4) showing that there is a clear misalignment between investors and their clients related to their behavioral profiles.

This misalignment can be explained not only by investors' overconfidence, but also by the trust that the client places in the practitioner. In fact, once all fees are considered, some studies find 2% investor underperformance relative to indexation. This evidence is difficult to reconcile with the fact that investors seek active managers to improve performance.

Gennaioli et al. (2015) develop an alternative view of money management based on the idea that investors do not know much about finance or are too nervous or anxious to make risky investments on their own, and hence they hire money managers and advisors to help them invest. Managers may have knowledge of how to diversify investments or even the ability to earn alpha returns, but in addition, they provide investors peace of mind. They refer to money doctors as families of mutual funds, registered investment advisors, financial planners, brokers, funds of funds, bank trust departments and others who give investors the confidence to take risks. The allocation of assets to managers is mediated not only by returns, but also by trust. Trust influences individual investment risk perceptions and equity premiums, and it may also explain the specific securities that individuals select (Olsen, 2012).

In any case, in the context of self-reported surveys, we must be cautious concerning such conclusions. To mitigate the potential

Table 1. Investor's profiles (BBK model).

Risk Profile/Confidence & Risk Aversion	Total	CFA	NO CFA	Men	Women
Adventurer (High Confidence, Low risk averse)	23%	22%	23%	26%	14%
Celebrity (Low Confidence, Low risk averse)	16%	17%	15%	19%	7%
Guardian (Low Confidence, High risk averse)	20%	20%	19%	17%	29%
Individualist (High Confidence, High risk averse)	42%	41%	42%	38%	50%
High Confidence	64%	63%	65%	64%	64%
Low Confidence	36%	37%	35%	36%	36%
Low risk averse	39%	39%	38%	45%	21%
High risk averse	61%	61%	62%	55%	79%

This table shows the frequency of self-perceived prevailing investor's profiles (question 2). The results are shown for the total population (column 2) and classifying investors based on education and gender variables (columns 3 to 6). Rows 6 to 10 show the distribution of investors in terms of confidence and risk aversion.

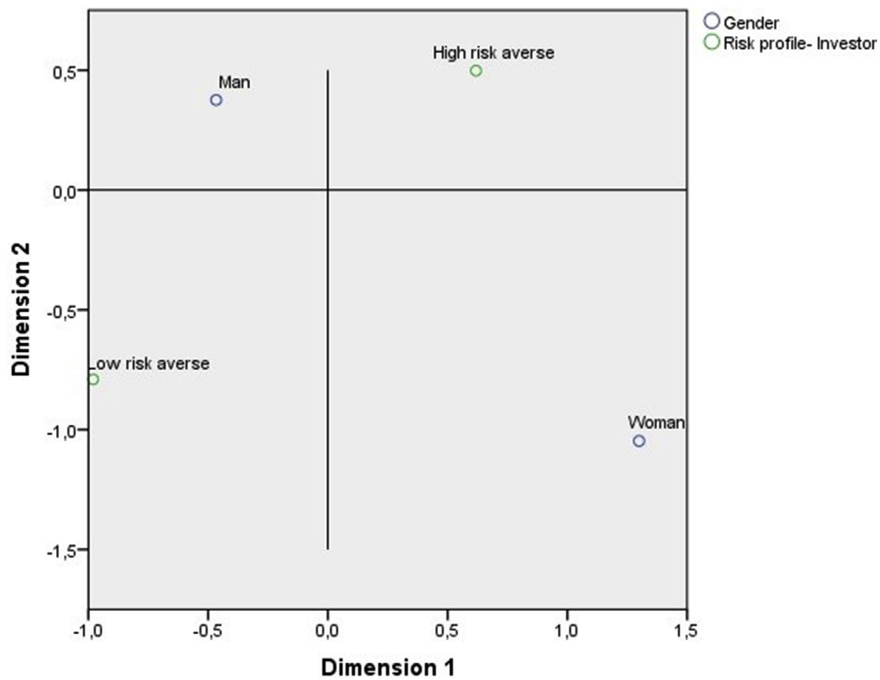

Figure 5. Perceptual Map: Investor Risk profile vs. Gender. This perceptual map shows the association between gender and the investor's risk profile.

Table 2. Client's profiles (BBK model).

Risk Profile/Confidence & Risk Aversion	Total	CFA	NO CFA	Men	Women
Adventurer (High Confidence, Low risk averse)	10%	13%	8%	10%	11%
Celebrity (Low Confidence, Low risk averse)	7%	4%	10%	5%	11%
Guardian (Low Confidence, High risk averse)	66%	69%	63%	67%	64%
Individualist (High Confidence, High risk averse)	17%	15%	19%	18%	14%
High Confidence	27%	28%	27%	28%	25%
Low Confidence	73%	72%	73%	72%	75%
Low risk averse	17%	17%	17%	15%	21%
High risk averse	83%	83%	83%	85%	79%

This table shows the frequency of prevailing clients' profiles according to the investor's perception (question 3). The results are shown for the total investors' population (column 2) and classifying investors based on education and gender variables (columns 3 to 6). Rows 6 to 10 show the distribution of client's profiles in terms of confidence and risk aversion.

misperception resulting from self-report surveys and to obtain a better understanding of the true nature of investors, we measure the actual investor sentiment through the investor's confidence index.

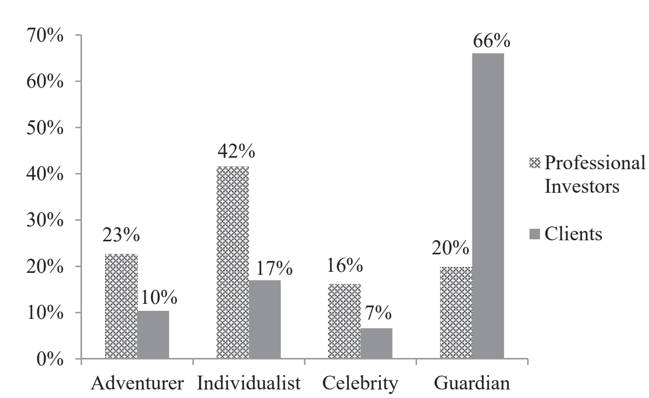

Figure 6. Professional Investor's and Client's Profiles (BBK). This bar chart represents the distribution of investors' and their clients' profiles following the BBK model and according to the investors' perception.

4.4. Modeling sentiment: institutional Investor's confidence index

We define the Institutional Investor's Confidence Index (IICI) based on the answer to sentiment questions. First, we analyze the relation between the confidence index and several investor's characteristics, including education (CFA accreditation), age, gender and the investor's profile. Our final goal is to outline a model for investors' sentiment based on the survey results.

We will use the two defined confidence indexes, IICI 1 and IICI 2, where IICI 2 includes the view of the macro environment. The average for IICI 1 is 49 (positive values reflect an optimistic outlook) and that for IICI 2 is 39.

Regarding normality, IICI 1 does not follow a normal distribution (Z Kolmogorov-Smirnov = 1.64, p-value = 0.01), but it does at a 10% significance level. IICI 2 follows a normal distribution (Z Kolmogorov-Smirnov = 1.09, p-value = 0.184).

4.4.1. Impacts of education, gender and age on investors' confidence index

There is homogeneity of variances between the confidence indexes (IICI 1 and IICI 2) and our different independent variables. Therefore, we can apply the Student's t-test or ANOVA to assess the impacts of education, age and gender on investors' confidence.

Regarding education, we find no impact of CFA accreditation or the hours of training in behavioral finance on the confidence index. Regarding CFA accreditation, we apply the Student's t-test for the equality of means and find no significant differences related to CFA accreditation for IICI 1 ($t = -0.16$, p-value = 0.87) or IICI 2 ($t = -0.29$, p-value = 0.78). Regarding the level of training in the field, we apply the one factor ANOVA and find no significant differences in the confidence index related to the hours of training for either IICI 1 (p-value = 0.86) or IICI 2 (p-value = 0.94).

Regarding gender, we find significant differences between men and women at the 10% significance level ($t = -1.92$; p-value = 0.058), where women (60) show a higher level of confidence than men (45), supporting our second hypothesis. However, there is no significant difference when applying IICI 2 ($t = -1.14$, p-value = 0.255). After applying the Mann-Whitney nonparametric test, we confirm these results for IICI 1 (U-Mann-Whitney = 810, p-value = 0.04) and IIC 2 (U-Mann-Whitney = 877, p-value = 0.12).

Regarding age, we find significant differences for both IICI 1 (p-value = 0.07) and IICI 2 (p-value = 0.02). In general, younger investors (less than 40 years old) show a lower level of optimism and confidence than the more experienced investors (40 or higher) with IICI 1 indices of 43 and 54, respectively. When applying the Kruskal-Wallis nonparametric test, we obtain the same results, validating our third hypothesis.

4.4.2. Modeling Investor's sentiment

For simplicity purposes, we generate a new confidence index obtained after extracting the most relevant information from the five sub-indices associated with IICI 1: the perspective index, the valuation index, the short-term recovery index, the long-term recovery index and the crash risk index. Our factorial analysis reduces the redundant information into a single variable, which is a linear combination of all variables; and forms the new confidence index (IICI Factorial) (KMO = 0.575, p-value of Bartlett test = 0.000). This new typified variable or factor presents a high correlation with the previously defined confidence indices (0.971, 0.931, respectively).

Using the factorial confidence index as the dependent variable, we develop a multiple linear regression model for the confidence index based on fourteen independent variables (Note 1 includes the list of variables) resulting from the answers to our survey, including gender (male or female), age (older or younger than 40 years), CFA accreditation (being a CFA Charterholder or not) and education in behavioral finance (education BF: having/not having learning experience in behavioral finance). Table 3 summarizes the list of variables considered for the Confidence Index Model:

The model is statistically significant ($R^2 = 0.24$, $F(14,91) = 2.7$ and p-value (F) = 0.013), and there is no heteroscedasticity (LM = 17.60, p-value = 0.67) or severe imperfect multicollinearity (the VIFs are all lower than 2). The model is therefore valid for identifying the main significant variables impacting investors' sentiment.

The results are shown in Table 4.

Gender and age have significant impacts on investors' sentiment of confidence index, validating our hypothesis 2 and 3 (H2 and H3). Female investors have a higher level of optimism compared to men (p-value = 0.028) and therefore may be more impacted by biased beliefs. This finding apparently contradicts the previous literature, which finds evidence of more optimism and overconfident behavior in men than women (Estes and Hosseini, 1988; Barber and Odean, 2001). However, according to Atkinson et al. (2003), there are no significant differences in the level of confidence related to gender, and Bliss and Potter (2002) find that women hold portfolios with more risk than men. Our research suggests that women are more risk averse (unconventional preferences) but are also more optimistic and confident (biased beliefs) than men.

Regarding age, younger investors have a lower confidence index than older investors (p-value = 0.056). This tendency to overweight personal experience is consistent with the existing literature and validates our third hypothesis (H3) (Greenwood and Shleifer, 2014).

It is interesting to note that the self-perceived investor's confidence profile is unrelated to the confidence index. In contrast, even if weak, there is some relation with the risk aversion profile (p-value = 0.157).

We find no significant differences related to the education variables, such as the hours of learning in behavioral finance or holding the CFA accreditation. This supports our fifth hypothesis (H5) and is consistent with research from Menkhoff and Nikiforow (2009), according to which behavioral biases are so deeply rooted in human behavior that they are hard to overcome through training.

5. Conclusions

According to the empirical evidence in this study, professional investors very significantly acknowledge the relevance of behavioral finance but also admit to having an insufficient level of training in the field (H1). This is mainly due to the lack of structure and clarity of the theory, as confirmed by our survey. Our research contributes to further systematization in the field of behavioral finance by analyzing the impacts of education, gender and age on investors' behavior and sentiment.

The potential self-perception bias in self-reported surveys compels us to be cautious with the conclusions of our research. However, the anonymous character of the surveys and the use of the institutional investor confidence index help us mitigate this effect. Additionally, considering cultural factors, the geographical scope of our survey, which was administered to practitioners in Spain, shall be extended to other countries to generalize our conclusions.

Based on the results of our survey, CFA Charterholders possess a superior level of education and awareness in behavioral finance and acknowledge being more impacted by herding behavior; whereas for non-CFA Charterholders, rational analysis prevails. The prevalence of herding or social conditioning is consistent with recent research (Menkhoff and Nikiforow, 2009).

Compared to men, women also have a higher level of education and consider themselves to be less impacted by irrational biases (H2). Regarding age, young investors overwhelmingly support the relevance of behavioral finance and acknowledge being more impacted by cognitive and emotional biases, but they have a similar lack of education in the field (H3).

The lack of education in behavioral finance, despite its increasing relevance for investors, is of the utmost importance from academic and professional points of view (H1). The implications for the functioning of financial markets and the need to be included in the financial studies curriculum should be carefully analyzed.

Regarding investors' profiles, practitioners view themselves as predominantly individualists and adventurers while they describe their clients as guardians. This entails a clear misalignment between the investors and their clients (H4), especially related to their level of confidence, which should be acknowledged by practitioners and represents a challenge for future research. This fiduciary role of the investor (Gennaioli et al., 2015) reinforces the significant need for increased education in behavioral finance. Olson and Riepe (2010) maintain that investors who leverage on behavioral finance theory receive more support and trust from their clients.

Gender is the only independent variable that has a significant impact on investors' profile as female investors view themselves as more risk-averse than men (H2). This lower risk tolerance from female investors is consistent with the previous literature (Olsen and Cox, 2001).

Finally, we establish a model to determine investors' sentiment, and we find significant differences related to gender and age factors. Female investors have a higher confidence index, which appears to contradict the existing literature describing male investors as being more optimistic and overconfident (Barber and Odean, 2001). More experienced investors also show a higher level of optimism, which is consistent with the previous literature indicating that practitioners tend to overweight their

Table 3. List of variables Considered for the Confidence Index Model:

Variable	Description / possible values
Gender	male or female
Age	younger or older than 40 years
CFA	being CFA Charterholder or not
Education BF	having/ not having learning experience in Behavioral Finance
DCF Value	relevance of DCF method to value a security
Confidence	high confidence (Adventurer or Individualist) or low confidence (Guardian and Celebrity)
Risk profile	high risk averse (Individualist or Guardian) or low risk averse (Adventurer or Celebrity)
Relevance BF	Behavioral Finance relevant/not relevant
Rational analysis	Relevance of rational analysis (values 1 to 5)
Cognitive bias	Relevance of cognitive biases (values 1 to 5)
Emotional bias	Relevance of cognitive biases (values 1 to 5)
Representativeness	Accuracy of statement (values 1 to 5)
Loss aversion	Accuracy of statement (values de 1 a 5)
Diff. profile	Difference between profiles (investor-client) (values 1 to 4)

This table shows the list of fourteen independent variables resulting from the answers to our survey, including Gender, Age, CFA Accreditation, and Education in Behavioral Finance (BF).

Table 4. A model for Investor's confidence (IICI factorial).

	Coefficient	Standard Dev.	T Student
Gender	-0.549 **	0.246	-2.228
Age	-0.408 *	0.210	-1.938
CFA accreditation	-0.042	0.239	-0.175
Education BF	0.055	0.201	0.272
DCFValue	0.198 *	0.107	1.851
Confidence	-0.115	0.259	-0.443
Risk profile	0.301	0.211	1.427
Relevance BF	0.399	0.391	1.021
Rational Analysis	-0.05	0.114	-0.437
Cognitive Bias	0.061	0.108	0.558
Emotional Bias	-0.073	0.105	-0.691
Representativeness	0.224 *	0.126	1.777
Loss Aversion	0.137	0.126	1.084
Difference Profiles	0.015	0.086	0.179

*p-value<0.1; **p-value<0.05; ***p-value<0.01

This table shows the results of the Multiple Linear Regression analysis for the Investor's Confidence Index based on fourteen independent variables including those related to Gender, Age and Education variables. Significant variables are identified on the second column (** for p-value < 0.05 and * for p-value < 0.10)..

personal experience (H3) with insufficient consideration of all available data (Greenwood and Shleifer, 2014).

The results of our survey show no impact of CFA accreditation, hours of training and acknowledged investors' profile on investors' sentiment. This is consistent with the research of Menkhoff and Nikiforow (2009), according to which the level of education in behavioral finance does not eliminate or reduce investors' irrational behavior (H5). Based on these findings and further empirical research, a comprehensive model of investors' sentiment has yet to be developed and represents an important line for future research.

Declarations

Author contribution statement

Manuel Gonzalez-Igual and Teresa Corzo Santamaria: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Antonio Rua Vieites: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability statement

Data included in article/supplementary material/referenced in article.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

Supplementary content related to this article has been published online at https://doi.org/10.1016/j.heliyon.2021.e06495.

References

Agarwal, S., Driscoll, J.C., Gabiax, X., Laibson, D., 2009. The age of reason: financial decisions over the life cycle and implications for regulations. Brookings Pap. Econ. Activ. 2009 (3), 51–101.
Akhtar, F., Thyagarj, K.S., Das, N., 2014. Developing an empirical framework for investment strategy based on BB&K five-way model. J. Manag. 4 (2), 47–63.
Ahmed, S., Sihvonen, J., Vähämaa, S., 2019. CEO facial masculinity and bank risk-taking. Pers. Indiv. Differ. 138, 133–139.
Atkinson, M.S., Boyce, S., Frye, M.B., 2003. Do female mutual fund managers manage differently? J. Financ. Res. 26 (1), 1–18.
Bailard, T.E., Biehl, D.L., Kaiser, R.W., 1986. Personal Money Management. Science Research Associates, Chicago, Ill.
Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Finance 61 (4), 1645–1680.
Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. J. Econ. Perspect. 21 (2), 129–152.
Barber, B., Odean, T., 2000. Trading is hazardous to your wealth: the common stock investment performance of individual investors. J. Finance 55 (2), 773–806.
Barber, B., Odean, T., 2001. Boys will be boys: gender, overconfidence, and common stock investment. Q. J. Econ. 116 (1), 261–292.
Barberis, N., Thaler, R.H., 2005. A survey of behavioural finance. In: Thaler, R. (Ed.), Advances in Behavioural Finance, II. Russell Sage Foundation and Princeton University Press, New York, pp. 1–75.
Beckmann, D., Menkhoff, L., 2008. Will women be women? Analyzing the gender difference among financial experts. Int. Rev. Soc. Sci. 61 (3), 364–384.
Bliss, R.T., Potter, M.E., 2002. Mutual fund managers: does gender matter? J. Bus. Econ. Stud. 8 (1), 1–15.
Brown, G., Cliff, M., 2005. Investor sentiment and asset valuation. J. Bus. 78, 405–440.
CFA Institute, 2013. The herding mentality: behavioral Finance and investor biases. Online Survey conducted to Professional Investors.
Chen, G., Kim, K.A., Nofsinger, J.R., Rui, O.M., 2007. Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors. J. Behav. Decis. Making 20 (4), 425–451.
Chuang, W., Susmel, R., 2011. Who is more overconfident trader? Individual versus institutional investor. J. Bank. Finance 35 (7), 1626–1644.
Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. J. Finance 66 (5), 1461–1499.
De Bondt, W., Muradoglu, G., Shefrin, H., Staikouras, S.K., 2009. Behavioral finance: quo vadis? J. Appl. Finance 18 (2), 7–21.
De Bondt, W., Mayoral, R.M., Vallelado, E., 2013. Behavioural decision-making in finance: an overview and assessment of selected research. Spanish J. Finan. Account. 157, 99–118.
Durand, R.B., Fung, L., Limkriangkrai, M., 2019. Myopic loss aversion, personality, and gender. J. Behav. Finance 20 (3), 339–353.
Edwards, W., 1968. Conservatism in human information processing. In: Formal Representation on Human Judgment. John Wiley and Sons, New York.
Estes, R., Hosseini, J., 1988. The gender gap on Wall Street: an empirical analysis of confidence in investment decision making. J. Psychol. 122 (6), 577–590.
Fama, E.F., 1965. Random walks in stock market prices. Financ. Anal. J. 21 (5), 55–59.
Fama, E.F., 1970. Efficient capital markets, a review of theory and empirical work. J. Finance 25 (2), 383–417.
Fenzl, T., Pelzmann, L., 2012. Psychological and social forces behind aggregate financial market behavior. J. Behav. Fin. 13, 56–65.
Fisher, K.L., Statman, M., 2000. Investor sentiment and stock returns. Financ. Anal. J. 56 (2), 16–23.
Gamble, K.J., Boyle, P.A., Yu, L., Bennett, D.A., 2014. Aging and financial decision making. Manag. Sci. 61 (11), 2603–2610.
Gennaioli, N., Shleifer, A., Vishny, R., 2015. Money doctors. J. Finance 70 (1), 91–114.
Glaser, M., Weber, M., 2010. Overconfidence. In: Baker, H.K., Nofsinger, J.R. (Eds.), Behavioral Finance. Investors, Corporations, and Markets. John Wiley and Sons, pp. 241–258.
Greenwood, R., Shleifer, A., 2014. Expectations of returns and expected returns. Rev. Financ. Stud. 27 (3), 714–746.
Grinblatt, M., Han, B., 2005. Prospect theory, mental accounting, and momentum. J. Financ. Econ. 78 (2), 311–339.
Hibbert, A.M., Lawrence, E.R., Prakash, A.J., 2012. Do finance professors invest like everyone else? Financ. Anal. J. 68 (5), 95–105.
Hirshleifer, D., 2015. Behavioral finance. Ann. Rev. Finan. Econom. 7, 133–159.
Hortacsu, A., Syverson, C., 2004. Product differentiation, search costs, and competition in the mutual fund industry: a case study of the S&P 500 Index funds. Q. J. Econ. 119 (2), 403–456.
Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. J. Finance 48 (1), 65–91.
Kahneman, D., Tversky, A., 1979. Prospect Theory: an analysis of decision under risk. Econometrica 47 (2), 263–291.
Korniotis, G.M., Kumar, A., 2011. Do older investors make better investment decisions? Rev. Econ. Stat. 93 (1), 244–265.
Lakonishok, J., Shleifer, A., Vishny, R.W., 1992. The impact of institutional trading on stock prices. J. Financ. Econ. 32 (1), 23–43.
Lamont, O.A., Thaler, R.H., 2003. Can the market add and subtract? Mispricing in Tech price carve-puts. J. Polit. Econ. 111 (2), 227–268.
Leitch, D., Sherif, M., 2017. Twitter mood, CEO succession announcements and stock returns. J. Comput. Sci. 21, 1–10.
Li, X., Sullivan, R.N., Xu, D., Gao, G., 2013. Sell-side analysts and gender: a comparison of performance, behavior, and career outcomes. Financ. Anal. J. 62 (2), 83–94.
Lin, Y.C.G., Chiu, C.L., Kang, E., 2010. Understanding online trading behavior: an example from common stock Investment in Taiwan. SBP (Soc. Behav. Pers.) 38 (5), 637–646.
Lundberg, M., Fox, P.W., Puncochar, J., 1994. Highly confident but wrong: gender differences and similarities in confidence judgments. J. Educ. Psychol. 86 (1), 114–121.
Markowitz, H., 1952. Portfolio selection. J. Finance 7 (1), 77–91.
Mehra, R., Prescott, E.C., 1985. The equity premium puzzle. J. Monetary Econ. 15 (2), 146–161.
Menkhoff, L., Nikiforow, M., 2009. Professionals' endorsement of Behavioral Finance: does it impact their perception of markets and themselves? J. Econ. Behav. Organ. 71 (2), 318–329.
Metawa, N., Hassan, M.K., Metawa, S., Safa, M.F., 2018. Impact of behavioral factors on investors' financial decisions: case of the Egyptian stock market. Int. J. Islam. Middle E Finance Manag.
Miller, M., Modigliani, F., 1961. Dividend policy, growth, and the valuation of shares. J. Bus. 34 (4), 411–433.
Mishra, K.C., Metilda, M.J., 2015. A study on the impact of investment experience, gender, and level of education on overconfidence and self-attribution Bias. IIMB Manag. Rev. 27 (4), 228–239.
Muralidhar, A., 2019. Can (financial) ignorance Be Bliss? Financ. Anal. J. 75 (1), 8–15.
NazariPour, M., Zakizadeh, B., Afshar, B., 2020. Investigating the investors' behavior in Tehran stock exchange based on BB&K five-way model. J. Psychol. New Ideas 6 (10), 1–14.
Nogueira, P.M., Pinho, c., 2020. A reappraisal of the causal relationship between sentiment proxies and stock returns. J. Behav. Finance.
Nofsinger, J., Patterson, F., Shank, C.A., 2018. Decision making, financial risk aversion, and behavioral biases: the role of testosterone and stress. Econ. Hum. Biol. 29, 1–16.
Nofsinger, J.R., Patterson, F.M., Shank, C.A., 2020. On the physiology of investment biases: the role of cortisol and testosterone. J. Behav. Finance.
Olsen, R., 2012. Trust: the underappreciated investment risk attribute. J. Behav. Finance 13 (4), 308–313.
Olsen, R., Cox, C.M., 2001. The influence of gender on the perception and response to investment risk: the case of professional investors. J. Psychol. Financ. Mark. 2 (1), 29–36.
Olson, B., Riepe, M.W., 2010. Using Behavioral Finance to improve the adviser–client relationship. Res. Found. Publ. 2010 (2), 125–154.
Ortiz, C., Sarto, J.L., Vicente, L., 2013. Herding behaviour in Spanish global funds' country allocations. Spanish J. Finan. Account. 157, 63–81.
Pompian, M., Longo, J., 2004. A new paradigm for practical application of behavioral finance: creating investment programs based on personality types and gender to produce better investment outcomes. J. Wealth Manag. 7 (2), 9–15.
Pompian, M., 2012. Behavioral finance and investor types. Private Wealth Manag. Featur. Artic. 2012 (1), 1–3.
Powell, M., Ansic, D., 1997. Gender differences in risk behavior in financial decision-making: an experimental analysis. J. Econ. Psychol. 18 (6), 605–628.
Prechter, R.R., 2001. Unconscious herding behavior as the psychological basis of financial market trends and patterns. J. Psychol. Financ. Mark. 2 (3), 120–125.
Samuelson, W., Zeckhauser, R.J., 1988. Status quo bias in decision making. J. Risk Uncertain. 1 (1), 7–59.
Schneider, H.L., Lappen, A.A., 2000. Behavioural Finance: old wine in a new bottle. J. Wealth Manag. 3 (2), 9–14.
Sharpe, W.F., 1964. Capital asset prices: a theory of market equilibrium under conditions of risk. J. Finance 19 (3), 425–442.
Shiller, R.J., 2000. Measuring bubble expectations and investor confidence. J. Psychol. Financ. Mark. 1 (1), 49–60.
Shiller, R.J., 2006. Irrational exuberance revisited. CFA Inst. Conf. Proceed. Q. 23 (3), 16–25.
Shukla, R., Singh, S., 1994. Are CFA Charterholders better equity fund managers? Finan. Anal. J. 50 (6), 68–74.
Tetlock, P.C., 2007. Giving content to investor sentiment: the role of media in the stock market. J. Finance 62 (3), 1139–1168.
Thaler, R.H., 1999. The end of behavioral finance. Financ. Anal. J. 55 (6), 12–17.
Thaler, R.H., 1985. Mental Accounting and consumer choice. Market. Sci. 4 (3), 199–214.
Thomas, T.C., Rajendran, G., 2012. BB&K Five-Way Model and investment behavior of individual investors: evidence from India. Int. J. Econom. Manag. 6 (1), 115–127.
Tversky, A., Kahneman, D., 1974. Judgment under uncertainty: heuristics and biases. Science 185 (4157), 1124–1131.
Wang, L., Niu, J., Yu, S., 2020. SentiDiff: combining textual information and sentiment diffusion patterns for Twitter sentiment analysis. Transact. Knowl. Data Eng. 32, 2026–2039.
Weißofner, F., Wessels, U., 2020. Overnight returns: an international sentiment measure. J. Behav. Finance 21 (2), 205–217.
Weinstein, N.D., 1980. Unrealistic optimism about future life events. J. Pers. Soc. Psychol. 39 (5), 806–820.
Xing, F.Z., Cambria, E., Welsch, R.E., 2018. Natural language based financial forecasting: a survey. Artif. Intell. Rev. 50, 49–73.
Xing, F.Z., Malandri, L., Zhang, Y., Cambria, E., 2020. Financial sentiment analysis: an investigation into common mistakes and silver bullets. In: Proceedings of the 28th International Conference on Computational Linguistics, pp. 978–987. Barcelona, Spain (Online).
Yadav, A., Vishwakarma, D.K., 2020. Sentiment analysis using deep learning architectures: a review. Artif. Intell. Rev. 53, 4335–4385.