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Overconfidence and disposition effect in the stock market: A micro world based setting

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ABSTRACT

Modern financial theory relies on the rationality assumption of investors even though, evidence suggests that market investors are affected by behavioural biases such as overconfidence and disposition effect. Overconfident investors perceive situations better than what they actually are, while investors exhibiting disposition effect tend to dispose winner shares and keep loser ones. However there is not clear causal relationship between both biases. We contribute to the literature about overconfidence and its relationship with the disposition effect, using a simulation model often named micro world, representing an artificial financial stock market. We propose a methodology combining qualitative (QCA) and quantitative (Logistic Regression) techniques to correlate transactions' outcomes with investors' characteristics. Results suggest that overconfidence is explained by gender, career and education level, while age, nationality, and profits are not significant variables. We also confirm that investors exhibiting disposition effect are more prone to be overconfident

1. Introduction

Modern financial economics assume that people behave with extreme rationality, but evidence suggests they may not. Furthermore, people's deviations from rationality are often systematic in practice. Attempting to explain this, behavioural finance relaxes the traditional assumptions of financial economics by incorporating observable, systematic, and very human departures from rationality into standard models of financial markets (Barber and Odean, 1999).

Behavioural finance studies the influence of psychology on the behaviour of financial practitioners and its subsequent effect on the markets for explaining why and how markets might be inefficient (Sewell, 2007). This field incorporates social cognitive and emotional biases to understand economic decisions and mostly how such decisions affect market prices, returns, and allocation of resources. It is primarily concerned with the rationality assumption of economic agents given that investors fall prey to their own and sometimes others' mistakes due to the presence of emotions in their financial decisions (Chandra, 2008).

There is wide research about specific biases affecting the behaviour of investors. For the purposes of this research, we only focus on overconfidence and disposition effect. Given that there are two common mistakes investors make: (i) excessive trading caused by overconfidence, and (ii) the tendency to disproportionately hold on to losing investments while selling winners which means those exhibiting the highest returns cause by the disposition effect (Barber and Odean, 1999).

Overconfidence does not necessarily mean that people are ignorant or incompetent. It rather means that their judgement and estimation of a situation is considered to be better than it actually is Pompian (2006), and several studies have shown that people tend to be overconfident in their financial decisions (Fischhoff et al., 1977).

In the particular case of financial markets, a common trait among investors is a general overconfidence of their own ability when it comes to investing in shares and deciding when exit a position (Subash, 2012). Nawrocki and Viole (2014) believe that one would generate a better understanding of financial market behaviour if one does not strictly consider the rationality assumption. This is the case of a common financial market anomaly known as disposition effect.

The disposition effect is characterized as investors commonly disposing winning shares and keeping losing ones, this due to their unwillingness to recognize loser shares. And in fact, the disposition

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effect describes a desire for investors to realize gains by selling stocks that have appreciated, but to delay the realization of losses (Statman et al., 2006).

However, there is still a vague quest when it comes to study the relationship between overconfidence and disposition effect. There is not agreement in which degree one bias could be explained in function of the other. And in case that there is not degree to explain one in function of the other, the question is how one could test their independency at all.

We believe that both biases do not act independently at all. In fact, given that overconfident investors tend to exhibit high trading volumes, this leads to changes in demand increasing prices, and such increase allows investors to perceive higher returns in the eventual case of selling their shares, which is in line with the disposition effect meaning that investors tend to sell winners and perceiving the appreciations of their investments will boost their overconfidence.

In this research, we developed a micro world simulating a financial stock market which generates primary data about investment dynamics of the participants. It is important to highlight that although micro worlds are relatively simple, they embody the essential characteristics of real world. And the main difference with a regular experiment is that the settings under which the micro world is conducted, is a simulation of reality.

This empirical data allows us to create a proxy variable for measuring overconfidence as a function of excessive trading, and a proxy variable for the disposition effect as a function of winner and loser shares according to Weber and Camerer (1998).

Our contribution to the literature on overconfidence and its relationship with the disposition effect relies on the methodological proposal that focuses on in cascading the results of the micro world. We first use them for conducting a Qualitative Comparative Analysis (QCA) to identify configurations in terms of causal conditions that produce a type of outcome in this case overconfidence. Then, with the results of the QCA we use Logistic Regression Analysis to quantify the effect of those causal conditions as independent variables explaining overconfidence, plus enquiring about how the disposition effect affects overconfidence.

It is important to highlight that in this study the big advantage of using QCA is that it allows to establish cross-case patterns taking into account the heterogeneity of the cases, with respect to their different conditions, and comparing them as configurations (Ragin, 2008). Therefore, the data from the micro world is being evaluated in an individual way, before conducting the regression analysis.

This paper is organized in five sections. Section 2 provides the necessary literature review to provide theoretical background on the concepts of overconfidence and disposition effect and attempts to relate both biases. Section 3 contains the methodology we propose. Section 4 presents the results and discussion, and finally, Section 5 concludes about the outcome of this research and proposes future research.

2. Literature review

People use simple mental strategies or heuristics to cope with the complexities of making estimates of probabilities and these heuristics can sometimes provide good estimates and reduce the effort required by the decision maker, however they can also lead to systematically biased judgements, and particularly regarding financial decisions, it could lead to serious loses (Goodwin and Wright, 2014).

Barber and Odean (1999) highlight two common mistakes investors make: (i) excessive trading caused by overconfidence, and (ii) the tendency to disproportionately hold on to losing investments while selling winners which means those exhibiting the highest returns cause by the disposition effect. This section reviews these two concepts and it also reports current research relating them.

2.1. Overconfidence

The concept of overconfidence derives from a large body of cognitive psychological experiments and surveys in which subjects, overestimate both their own predictive abilities and the precision of the information they have been given. People are poorly calibrated in estimating probabilities of events they think are certain to happen. In short, people think they have better information than they actually do.

Overconfidence does not necessarily mean that individuals are ignorant or incompetent, rather, it means that their judgement and estimation of a situation is considered to be better than what it actually is (Pompian, 2006).

Bar-Yosef and Venezia (2006) distinguish three main types of overconfidence. The first type is overprecision or calibration of probabilities. People are overconfident if the precision of their estimate is too high, or put differently if they attach too low probability to the event that they may be wrong (Alpert and Raiffa, 1982).

A second type of overconfidence is overestimation or optimism. Researchers find that people overestimate their ability to do well on tasks, they are unrealistically optimistic about future events, they expect good things to happen to them more often than to their peers and they are even unrealistically optimistic about pure chance events (Bar-Yosef and Venezia, 2006).

The above is linked to the third type of overconfidence is overestimation or over placement. Most individuals see themselves better than others see them (Biais et al., 2004). People rate their abilities and their prospects higher than those of their peers. This refers to an inclination to overestimate performance either in comparison with the actual performance or in comparison with the performance of others (Pikulina et al., 2017). In this research, we study the third type of overconfidence as overestimation of investors in the stock market.

Chandra (2008) explores the impact of behavioural factors and investor's psychology on their financial decisions, examining the relationship between investor's attitude towards risk and behavioural decision making. Findings state that unlike the classical finance theory suggests, individual investors do not always make rational investment decisions and their investment decision-making is influenced, to a great extent, by behavioural factors leading to biases such overconfidence which must be taken into account as risk factors while making investment decisions.

A major consequence of overconfidence was found by Barber and Odean (1999) which state that overconfident traders tend to trade high volumes, causing that on average these investors receive significantly lower yields than the market. Psychologists have determined that overconfidence causes people to overestimate their knowledge, underestimate risks, and exaggerate their ability to control events. And investments in the stock market is precisely the financial task at which people exhibit the greatest overconfidence (Baker and Nofsinger, 2002).

Interestingly, researchers explain the presence of overconfidence by individual characteristics of investors such as age, education, income, investment portfolio, and other demographic factors (Bar-Yosef and Venezia, 2006; Barber and Odean, 2001). However, before explaining this bias, the quest relies in how to measure it. Several studies have mainly used three measures: (i) intervals of confidence, (ii) stock turnover rate, and (iii) actual average number of transactions.

2.1.1. Intervals of confidence

Intervals of confidence highlight in the literature as a popular measure for overconfidence. However, this usual way of measuring overconfidence must be treated with caution (Glaser and Weber, 2007).

Intervals of confidence require decision makers to provide lower and upper bound estimates of answer about several binary choice general knowledge questions (Blavatskyy, 2009). Subjects are instructed to state intervals such that their own confidence is between these stated bounds, subject to a confidence level that is requested by the experimenter (Langnickel and Zeisberger, 2016).

A typical finding when using confidence intervals, is that subjects appear overconfident for difficult questions (percentage of correct answers below approximately 75%) and underconfident or well calibrated for easy questions (Blavatskyy, 2009). This became known as the hard/easy effect (Fischhoff et al., 1977), which can be eliminated when researchers carefully control for the scale end effects (the upper and the lower bound on confidence scores) and linear dependency (Juslin et al., 2000).

In addition, recent studies have shown that groups with different requested confidence levels achieve the same average hit rate because they do not adjust the width of their interval estimates (Teigen and Jørgensen, 2005). Langnickel and Zeisberger (2016) confirm weaknesses of the interval measure, and they show that decision makers not even adjust their frequency judgements to different levels confidence requested.

2.1.2. Turnover rate

In recent years and in the context of financial decisions, overconfidence has been measured by excessive trading. Theoretical models are still used to predict that overconfident investors will trade more than rational investors. Glaser and Weber (2007) directly test this hypothesis by correlating individual overconfidence scores with several measures of trading volume of individual investors.

Barber and Odean (1999), showed for a large sample of individual traders that overconfident investors trade more than what it is rational and that doing so, lowers their expected utilities. The authors argued that the returns on the individuals' portfolio did not justify the high transaction costs. Moreover, they suggested that the returns on stocks that the investors purchased, were lower than those they sold to make those purchases. However, there is uncertainty about whereas indicators of overconfidence could be symptoms of other biases. And moreover, the definition of excessive trading is somewhat nebulous (Bar-Yosef and Venezia, 2006).

In this way, the stock turnover rate seems a suitable proxy variable for the level of overconfidence (Barber and Odean, 1999; Odean, 1998; Statman et al., 2006), which is calculated for each period, and then averages those values for each investor. The main disadvantage of this measure is that the average turnover rate would be the same for each of the investors. If then, the average turnover rate is used to rank the overconfidence of investors, then investors are likely to be identified with the same characteristics and grouped together. However, a given investor might possess certain information in a period, which would explain the large number and high concentration of the transactions.

2.1.3. Actual average number of transactions

Another criterion used to rank and classify the overconfidence of investors is the actual average number of transactions proposed by Ho (2011). This measure consists of the division between total number of transactions and the actual number of active periods with transactions. Investors with frequent trading and investors with general trading will not be classified into the same group, which should mitigate the frequency of type I and type II errors Ho (2011).

Ho (2011) proposes to replace the turnover rate with the actual average number of transactions—AANT:

$$AANT = \frac{\sum_{t=1}^{T} Number\ of\ Shares}{Number\ of\ active\ periods} \quad (1)$$

In sum, overconfidence is not an explicit trait, and both questionnaire surveys and laboratory studies are subject to errors (Deaves et al., 2009, 2010). Reason why we believe that using the actual average number of transactions as a proxy for measuring this bias allows us to characterize overconfidence of stock market investors.

2.2. Disposition effect

Another common bias that afflicts individual investors when they sell stock from their portfolio is called the disposition effect. Suppose an investor holds two stocks. One of the stock has increased its value (Winner) and the other stock has decreases its value (Loser), both compared to its respective initial price. A plausible way to formulate the selling choice is that the investor could account to sell the winner stock as a successful investment for his/her own records, or alternatively, the investor could account to sell the loser stock as a failure for his/her investment records. If selling stock is framed as a choice between giving the investor pleasure or causing pain, once could say that the investor may certainly sell the winner rather than the loser (Kahneman, 2011). The disposition effect is an instance of narrowing framing. The investor expects gains in every investment he/she makes. However, a rational agent would have a comprehensive view of the portfolio and sell the stock that is least likely to do well in the future, without considering whether it is a winner or a loser.

Disposition effect is a common irrational behaviour that investors exhibit in the stock market (Ho, 2011), and while prospect theory suggests the hypothesis that investors display a disposition to sell winners and ride losers, standard financial theory suggests the opposite (Shrefrin and Statman, 1984)

Kahneman and Tversky (1979) offer an explanation for the disposition effect. These authors find that people express an attitude of risk aversion when facing profit, but a risk-seeking attitude when facing loss. Their subsequent research also finds that people value loss twice as highly as they do profit, clearly demonstrating that people exhibit loss aversion.

To measure the disposition effect, Weber and Camerer (1998) proposed the following proxy:

$$DE = \frac{S_{+} - S_{-}}{S_{+} + S_{-}} \quad (2)$$

This proxy defines a disposition coefficient for each subject calculated as the difference between winners S_{+} and losers S_{-} shares sold, normalized by the total number of shares sold. If the disposition coefficient is zero or negative one can say that there is not disposition effect and if it is positive one can say that the disposition effect exists.

2.3. Relationship between disposition effect and overconfidence

Odean (1998) finds that the overconfidence causes investors to behave irrationally, which leads to poor performance, and concludes that overconfident people often suffer considerable costs and losses. On the other hand, regarding the disposition effect, Statman et al. (2006) found that turnover rates of stocks and lags of stock returns present significant positive correlation in the context of financial markets in USA. This implies a relationship between both biases however there is not clear evidence about their relationship in terms of causation.

Ho (2011) uses as depend variable the disposition effect which is explained by the level of overconfidence and other variables. One of the hypothesis is that the disposition effect is more significant in traders with higher degrees of overconfidence, and findings suggest that there is a difference in the disposition effect among investors with different levels of overconfidence and in fact, there is a positive correlation between the degrees of confidence and the disposition effect.

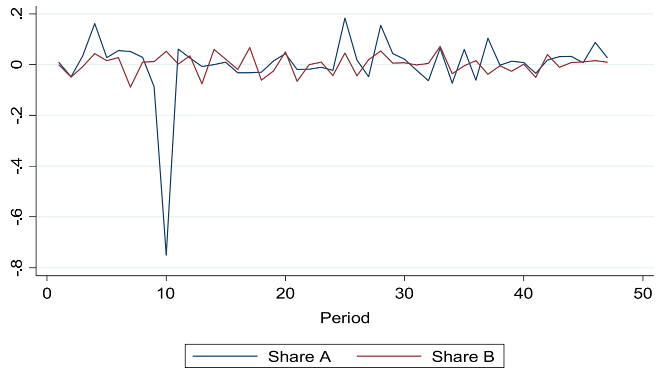

Fig. 1. Historical return for Share A and B.

Other studies have focused on each bias in a separately way. Barber and Odean (1999) tested both biases separately using secondary data sets and they found, that as predicted, investors tend to sell their winners and hold their losers. They also found that because of overconfidence, investors trade to their detriment.

In both cases, the behavioural theories tested offer insights into trading volume. The disposition effect says that investors will generally trade less actively when their investments have lost money while overconfidence theory suggests that investors will trade more actively when their overconfidence is high.

It seems that both overconfidence and disposition biases explain the positive relationship between trading activity and returns. Positive returns lead to an increase in trading volume and this boosts the confidence of investors, while the disposition effect, also implies that volume follows returns, because investors are reluctant to sell after accruing poor returns, and also eager to lock in gains after an increase in stock prices.

Hence, both the overconfidence and disposition effects could result in a positive relationship between trading activity and prior returns. One particular consequence of this is that it is quite difficult to empirically differentiate between the overconfidence and disposition effects based purely upon a positive return–volume relationship (Chou and Wang, 2011).

It seems that there is still a vague quest when it comes to study the relationship between overconfidence and disposition effect. First, we wonder until which degree one bias could be explained in function of another bias. Also, which is the right causal relationship. And in case that there is not degree to explain on bias in function of the other, the question is how one can test their independency at all.

3. Data and methods

This section contains four subparts. First, we explain the methodological approach named micro worlds and we present its characteristics. Second, we describe the sample and software used in this study. Third, we discuss the data collected and measures used, and finally, we present the description of QCA methodology application, explaining the inputs used in QCA and logistic regression. Fig. 2 outlines our methodological approach.

3.1. Micro worlds

Micro worlds are simulation models that allow users to make decisions and observe the effect of such decisions through several performance indicators, and then allowing them to make a new decision for several periods (Morecroft, 1988; Senge, 1990).

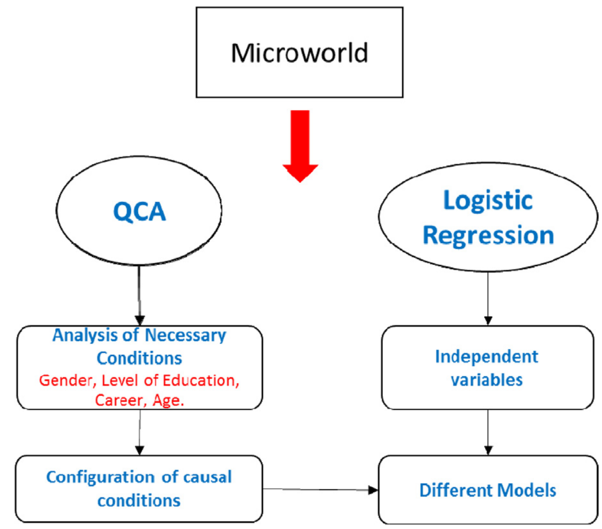

Fig. 2. Methodology of analysis.

The use of micro worlds, represents a compromise between experimental control and realism, and it enables researchers to conduct experimental research within the dynamic, complex decision-making situations that characterize dynamic decision making and complex problem solving (Funke, 1995).

Micro worlds provide the experimental control needed to develop explanations of decision making processes rather than task specific descriptions of decision making, and thereby can lead to results that are generalizable across a variety of dynamic decision-making tasks (Gonzalez et al., 2005). In fact, micro worlds have been hailed as tools that bridge the gap between laboratory and field research (Brehmer and Dörner, 1993).

In our particular case, the micro world is a representation of an artificial financial market with the following characteristics:

- There is capital market with $n = 2$ risky assets, each with random rates of return.
- The investor joins the market at time 0 with an initial wealth $W_0 = 10.000$ euros, and can allocate either all or part of it among the two assets in order to maximize its return.
- The investor is only interested in composing a portfolio and under the settings of this micro world, the shares acquired in the period t are automatically sold at market price in the time $t + 1$.
- The wealth can be reallocated among the two assets at the beginning of each of the following t consecutive time periods.
- The rates of return of the risky assets at time t within the planning horizon are denoted by a vector $r_t^n = \left[r_1^n, r_2^n, \ldots., r_t^n\right]'$
- The time frame for the investments is $t = 1, \ldots., 13$.
- Time series data was collected for two companies that will be named A and B. This is real information from the two big companies in the American stock market and the information ranges from June 2013[1] to May 2017[2] (*See* Fig. 1).

The historical information is presented to the participants and then they must decide the quantity of shares to buy in case they want to invest. After the participant inserts the quantity of shares desired to buy, the next period starts and the returns of the previous

[1] Period 1 in Fig. 1.

[2] Period 47 in Fig. 1.

period are presented. It is important to highlight that this is not a simultaneous setting in which prices adjust given demand and supply, so the prices for the 13 periods of the micro world were forecasted using an ARIMA pricing model.

3.2. Sample and software

The participants of micro world were mainly Bachelor, Master, Ph.D., and Postdoc students. We managed to gather 77 participants of different latitudes of Latin America and Europe. The micro world[3] was programmed and conducted with the software Z-Tree (Fischbacher, 2007), which is useful for developing and conducting economic experiments.

The information provided to participants involves historic information about the behaviour of the price and the return of each share, the average price and return for each share, and their current wealth. The decisions to be made by the participants is about the number of shares either A or B they want to buy in the market, in case they want to invest. Once they made their decision, the application shows the results of all variables for the current period. The information is then updated for the following periods.

3.3. Data collected, and measures used

The micro world allowed to collect primary data about the characteristics of participants and the decisions made by them in each of the rounds. The demographic variables collected were: level of education, age, gender, nationality, and field of studies. The information provided by each participant was the type and number of shares bought in each period.

The measures that were calculated based on information provided by the participants were: actual average number of transactions, dummy variable of overconfidence, and disposition effect variable.

Following Ho (2011), we calculated actual average number of transactions for each share, and with these numbers we proposed a scale of overconfidence. Using this criterion, we ranked and classified the overconfidence of investors. If an investor exhibits overconfidence for at least one of the shares, he/she is classified as overconfidence investor.

Based on work of Weber and Camerer (1998), we constructed our own measure of the coefficient of disposition effect in each period for each investor, so:

$$DE(t) = \frac{\%Winner\ Sold_t - \%Losser\ Sold_t}{\%Winner\ Sold_t + \%Losser\ Sold_t} \tag{3}$$

We classify the two possible shares one as winner and the other one as loser by comparing the percentage change in their return for period $t-1$. Once the winner and the loser are chosen, we calculate the $\%Winner\ Sold_t$ which is the percentage change of the winner share sold in period t and $\%Losser\ Sold_t$ which is the percentage change of the loser share sold in period t.

In our micro world, the participants could only buy shares in each period, and these shares were automatically sold in period $t+1$. Therefore, considering that the selling decision was not in the hands of the participants, and in order to still calculate a disposition effect, we propose to analyse the percentage change in the acquisition of shares of each type from one period to the next one. If the percentage change of shares bought from one period to the next is negative, it is because the investor decided to have less of that specific share and we assume this as a sale.

[3] In case you need to replicate this micro world, the programme is available up to request.

Although, in our case the disposition effect can vary from one period to other, we have:

$$DE(t) = \begin{cases} DE > 0 & \text{Disposition Effect} \\ DE \leq 0 & \text{No Disposition Effect} \end{cases} \tag{4}$$

The interpretation of this measure is in the fashion Weber and Camerer (1998).

3.4. Methodology of analysis

To explain overconfidence of investors and confirm its connection with the disposition effect, we propose a methodology that involves Qualitative Comparative Analysis (QCA) and Logistic Regression, which uses as input the primary data that has been generated using the micro world.

Qualitative Comparative Analysis (QCA) is used to determine different configurations composed by causal factors that produce the same outcome (overconfidence). QCA differs from other data analysis methods in its focus. Instead of looking for the strongest net effect or explanatory power of variables, QCA focuses in how different conditions can be combined and whether there is only one combination or several different combinations of conditions (causal recipes) of generating the same outcome (Ragin, 2008).

The causal factors used are demographic variables of the investors. The quantitative technique used (logistic regression) is used to estimate the odds ratio on overconfidence of each independent variable (causal factor) previously identified, plus the disposition effect to assess its relationship with overconfidence.

3.4.1. Qualitative Comparative Analysis (QCA)

QCA is a technique that allows identifying different configurations of factors (causal conditions) that may lead to the same outcome (Ragin, 2008). In this case, the outcome is the overconfidence which is represented by a dummy variable.

There are three main advantages of this methodology. First, QCA allows to study causal conditions, which can be necessary or sufficient, or both. Necessity and sufficiency are indicated when certain set relationships exist. Necessity means that the outcome is a subset of the causal condition. While sufficiency means that the causal condition is a subset of the outcome. Second, QCA allows to identify different combinations of causal conditions that cause the same outcome. Finally, QCA facilitates a form of counterfactual analysis (Ragin, 2008). For this study, we use the fsQCA 2.0 software, which is free software designed by Ragin in 2008. This software is used to perform fuzzy-set analysis, it means QCA uses variables that present membership scores to vary between 0 and 1.

In our case, the causal conditions are gender, level of education, career and age of participants in the micro world. An important requirement in QCA is the use of qualitative variables. Given that the age was a continuous variable, we did a logistic regression between overconfidence the age and the age squared, in order to establish a quadratic relationship. We found that overconfidence and age showed an inverted u-shaped relationship, evidencing that overconfidence increases with age, but to some extent, from which it begins to decrease. We calculated this cut-off point and the value was 31 years old. Therefore, we created for age, a dummy variable named Minor 31, that takes the value of 1 if the participant is younger than 31, and zero in another case.

A truth table sorts cases by the combinations of causal conditions, with some rows containing many cases, and some rows just a few and/or no cases. An algorithm based on Boolean algebra is used to logically reduce the truth table rows to simplified combinations. The number of rows is reduced considering: (i) the minimum number of cases required for a solution, and (ii) the minimum level of consistency of a solution.

Table 1
Descriptive statistical analysis of samples.

Variables	Mean	Standard deviation	Minimum	Maximum
Overconfidence	0.75	0.43	0	1
Age	24.96	5.70	18	49
Gender	0.68	0.47	0	1
Social Science	0.79	0.41	0	1
Postgraduate	0.22	0.41	0	1
Latin	0.49	0.50	0	1
Europe	0.44	0.50	0	1
Disposition effect	−0.15	0.70	−1	1

The result of QCA is focused on identify different configurations of causal conditions that produce the same outcome. In our case, we used these configurations as possible models in the logistic regression, to quantify the marginal effect on overconfidence of each causal condition.

There are two measures of model fit: consistency and coverage. Consistency refers to the degree to which cases correspond to the theoretical relationships expressed in a solution (Fiss, 2007). Perfect consistency is shown with scores of 1 while a score of 0 indicates perfect inconsistency. A causal condition is necessary if its consistency score is higher than 0.9 (Schneider et al., 2010). Solution coverage measures the empirical importance of the solution as a whole, while the raw coverage measures the explanatory power of an individual configuration (Ragin, 2006).

According to Ragin (2008) a minimum consistency of 0.8 is sufficient to indicate goodness of fit and a minimum coverage of 0.45 is necessary to evidence the empirical importance of the solution.

3.4.2. Logistic Regression

In linear probability model stated by Wooldridge (2010), it is assumed that the probability of response is linear in a set of parameters, β. A class of binary response models follows the form:

$$P(y=1|x) = G\left(\sum_{k=0}^{k=n} \beta_k X_{ik}\right) \tag{5}$$

Where G is a function that assumes values strictly between zero and one: $0 < G(z) < 1$, for all real numbers z. This ensures that the estimated response probabilities are strictly between zero and one.

Several nonlinear functions for the G function have been suggested to ensure that the probabilities are between zero and one. The two that will be studied here are used in most applications (along with MPL). In the logit model, G is the logistic function:

$$G(z) = \frac{\exp(z)}{(1-\exp(z))} = \Delta(z) \tag{6}$$

Which is between zero and one for all real numbers z. This is the cumulative distribution function for a standard logistic random variable.

4. Results

This study involved seven variables of interest related to overconfidence, age, gender, career (social science), education level (postgraduate), location (Latin America and Europe), and disposition effect. Table 1 presents the main descriptive statistics of these variables.

Given that the micro world was played by 77 participants, it is observed that 68% from them were males. The average age of sample was 25 years old and was concentrated between 25 and 30 years old. Most of 88% of the participants were bachelor students from the field of social science. And almost half of the participants were Europeans and the other half from Latin America.

Table 2
Analysis of Necessary Conditions for Overconfidence Bias.

Conditions tested [4]	Consistency	Coverage
Postgraduate	0.24	0.82
∼Postgraduate	0.76	0.73
Minor 31	0.53	0.74
∼Minor 31	0.47	0.77
Gender (Male = 1)	0.77	0.86
∼Gender (Female = 0)	0.22	0.52
Latin	0.48	0.74
Europe	0.45	0.76
Social Science	0.83	0.79
∼Social Science	0.17	0.63

Table 3
Configurations of causal conditions leading overconfidence.
Source: Authors' elaboration based on software FsQCA

Condition	1	2
Postgraduate	•	
Gender (Male = 1)		•
Social science		•
Consistency	0.82	0.92
Raw coverage	0.24	0.62
Unique coverage	0.16	0.53
Solution consistency	0.76	
Solution coverage	0.90	

Note: •peripheral condition (present). The format of presenting the results from the fuzzy-set analysis is based on Ragin and Fiss (2008).

4.1. Qualitative comparative Analysis—QCA

In the case of QCA we used four causal conditions to explain the outcome, which is the overconfidence of participants in the micro world. The causal conditions are the different demographic variables: Minor 31, career (social science), education level (postgraduate), and location (Latin America and Europe),

For these causal conditions defined in this research, we perform tests to verify consistency or necessity of them. Table 2 presents this analysis for all causal conditions that produce high overconfidence bias on financial takers.

None causal condition is necessary because its consistency score is lower than 0.9. However, given that postgraduate, gender and social science presents the highest values of consistency, 0.76, 0.77 and 0.83, respectively, these causal conditions were chosen to conform the configuration that explain the overconfidence. Also, these variables were chosen as independent variables in the logistic regression model. Table 3 presents the configuration of causal condition for Overconfidence Bias.

The analysis suggests two configurations of conditions that predict overconfidence bias. This solution presents a consistency of 0.76, indicating a goodness fit. The coverage is 0.90 showing the empirical importance of the solution.

This solution can be written as a Boolean equation so:

$$Overconfidence = postgraduate + gender * social\ science \tag{7}$$

In this equation, each additive factor represents a configuration of causal conditions associated with overconfidence. The star (*) represents the Boolean logic term AND. The plus sign (+) represents the Boolean term OR.

Configuration 1 means that overconfidence is presented by investors that present postgraduate studies, this result is according to Mishra and Metilda (2015), who found that overconfidence increases with investment, experience and education.

[4] Following the QCA terminology and convention, the symbol (∼) represents the negation of the characteristic.

Configuration 2 means that overconfidence is explained by gender and social studies. In this case, gender is one of the variables with the most empirical evidence in the study of overconfidence bias. In particular, Barber and Odean (2001) found that the men are overconfidence than women, and as mentioned by Mishra and Metilda (2015), the effect of overconfidence is stronger for men. In other way, the investor's career would also have effects on overconfidence bias, findings suggest that students in business related academic disciplines (political science, law, economics and business administration) exhibit the highest confidence levels (Schulz and Thöni, 2016).

The solution consistency meets the threshold values, 0.82 and 0.92, respectively, indicating that data adjust well to the configurations.

Given the necessary conditions analysis we chose three qualitative variables that reported the greatest consistency with the result of overconfidence. Such variables were: (i) gender, (ii) postgraduate and (iii) social science, which will be used as independent variables in the logistic regression, which is presented below.

In is important to highlight that in addition to these three qualitative variables to explain why an investor acts under the overconfidence bias, the coefficient of effect disposition will be analysed as an independent variable.

4.2. Logistic regression

The benchmark logistic regression that we used was:

$$P(Overconfidence_{it} = 1) = \beta_0 + \beta_1 Postgraduate_{it} + \beta_2 Gender_{it} + \beta_3 Social\ Science_{it} + \beta_4 DE_{it} + \varepsilon_{it} \quad (8)$$

Where:

$Overconfidence_{it}$ takes the value one if the participant i presents overconfidence in at least one of the shares, in the period t, and zero in other case.

$Postgraduate_i$ takes the value one if the participant i presents education level higher than Bachelor zero in other case.

$Gender_i$ takes the value one if the participant i is male and zero in other case.

$Social\ Science_i$ takes the value one if the participant i has a career related to social science and zero in other case.

DE_{it} refers to the Disposition Effect index proposed by Weber and Camerer (1998). If the value of the disposition effect for the participant i in the period t is negative, then one can say that no disposition effect was observed, and if the value of this index is greater than zero then the disposition effect is present.

Taking into account that we have a panel data, we used Hausman test in order to decide between random and fixed effect estimators. This test compares the β obtained by means of the fixed effects estimator and random effects, identifying whether the differences between them are significant or not. The result of this test was that there is no correlation between the individual effects and the explanatory variables, indicating that the random estimator must be chosen.

Table 4 presents the odds ratio resulting from a logistic regression with random effects. Models 1 and 2 are estimated through a cross-sectional data base using the configurations resulting from the QCA, and model 3 is estimated using the data panel including the coefficient for the disposition effect.

Model 1 is not significant, having only the educational level as an independent variable we cannot explain the probability that an investor exhibits overconfidence. On the other hand, Model 2 reports significant coefficients with a Pseudo R^2 of 17%, and gender mainly explains the bias of overconfidence. This implies that the probability that a man is overconfident is 8.45 times greater than the probability of a woman being overconfident. Likewise, the probability of being overconfident of those who have studied careers focused on social sciences is 4.6 times greater than the probability of those participants who have studied carries from another field.

Table 4
Logit: Odds ratio.

	Dependent variable: Overconfidence		
Independent	1	2	3
Postgraduate	1.69	2.79***	
	(0.19)		(0.61)
Gender		8.45***	9.34***
		(5.49)	(1.72)
Social science		4.26**	5.27***
		(3.10)	(1.11)
Disp Eff			1.21 *
			(0.14)
Pseudo R2	0.01	0.17	0.19
Chi2	0.61	14.47***	163.08***
Log likelihood	–	–	–
	42.71	35.79	451.98

*** $p < 0.001$, * $p < 0.10$. Standard Error in parenthesis.

Table 5
Logit: Average marginal effects of all covariates.

Independent variables	Model 3
Postgrade	0.14963
Gender	0.32602
Social Science	0.24252
Disposition effect	0.02839

Model 3, in addition to the three categorical variables selected, the disposition effect was included, and the model adjustment improved, reporting a Pseudo R^2 of 19%. The variable that continues to have the greatest explanatory power remains to be the gender with an odds ratio of 9.34 followed by social science with an odds ratio of 5.27. Unlike model 1, including postgraduate variable in the complete model gives explanatory significance and can be interpreted as the probability that investors with postgraduate studies have 2.79 more probability of being overconfidence compared to the others. Regarding the disposition effect, this is in line with previous studies, and the probability of being overconfident is 21 percent higher in the investors exhibiting disposition effect than those who do not.

All coefficients, excluding the disposition effect coefficient, are significant at 1%, and the coefficient of disposition effect is significant at 10%. Finally, we report the in Table 5 the average marginal effects of all covariates for the model 3. We can observe that the gender is an important determinant of overconfidence bias, being a man increases the probability of present the overconfidence bias by 32.6 percent compared to women. Keeping the other variables at their means, an increase in the disposition effect coefficient generates that the probability of an investor to be overconfident is 2.8 percent higher compared to investors without being affected by the disposition effect.

It is important to say that we did a logit model, which was not reported in tables, this model included all the independent variables we had collected such as age, nationality, profits, wealth and this model did not reach an R^2 of 0.21. Only increased the adjustment by 2%, but at the same time some of the variables lost their significance. Therefore, the specification shown by the QCA analysis was the model that is more consistent with data and theory.

5. Conclusions and implications

Much of the research discussed in the literature review reports patterns regarding the behaviour of financial market investors affected by overconfidence in terms of their excessive trading and disposition effect in terms of disposing winner shares and keeping losers. However there is not agreement about the causal relationship between these two biases.

To contribute to research in the field, we have developed a micro world representing a stock market in which participants make investment decisions for a series of periods, plus also demographic information about the participants. Once the primary data was obtained, we proposed a methodological approach involving qualitative comparative analysis (QCA) and quantitative techniques (Logistic Regression) to identify and quantify explanatory variables for overconfidence and characterize its relationship with the disposition effect. Results suggest that overconfidence is explained by gender, career and education level, while age, nationality, and profits are not significant variables.

We believe that as mentioned in the literature review, overconfident investors tend to exhibit high trading volumes, which leads to changes in demand increasing prices, and such increase allows investors to perceive higher returns in the eventual case of a selling shares, which is in line with the disposition effect in which investors tend to sell winners and perceiving the appreciations of their investments will boost their overconfidence. And our results confirm that investors exhibiting disposition effect are more prone to be overconfident.

As limitation of this study, we believe that the settings under which the micro world works are still simple. There are some assumptions that could be relaxed for improving the micro world itself. Also, we only managed to gather 77 participants and we did not involve participants that work as professional traders.

For future research, we suggest to improve the settings of the micro world. This new version should be a simultaneous game in which prices will be composed given the interactions in the market. Also, we believe that to generate more representative results about stock market investors, it would be desirable to have real stock market investors playing the game and, it would also be desirable to increase the sample size.

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