DYNAMIC MECHANISMS BEHIND OVERCONFIDENT STOCK MARKET INVESTORS

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TABLE OF CONTENTS

TABLE OF FIGURES

TABLE OF TABLES

1. INTRODUCTION

1.1 Background

In the field of finance, two schools of thought attempt to explain investors behaviour. In one hand, modern portfolio theory states how markets would work in an ideal world, while on the other hand, behavioural finance focuses on how financial markets work in the real world.

The Efficient Market Hypothesis EMH proposed by Fama (1970), states that an efficient market fully reflects all available information, therefore price changes must be unforecastable if they are properly anticipated, i.e. if they fully incorporate the expectations and the information of all market participants (Getmansky & Papastaikoudi, 2002). In fact, in an efficient market at any point in time, the actual price of a financial product will be a good estimate of its intrinsic value. And it is in this efficient market where rational agents meet to maximize their profit in a competitive environment, and each of them try to predict future market values of individual financial products, using current information which is almost freely available to all participants (Fama, 1970).

Portfolio theory relies its roots on the efficient market hypothesis, it is the area of finance that deals with the theoretical problems related to the allocation of wealth among different available investments in a financial market in which the exchange of financial products occurs (Szegö, 1980). Such financial products exhibit expected returns and liquidity, and these two features are key components for forming investment decision mostly known as portfolios (Heffernan, 1990). Traditional approaches to portfolio composition assume that i) investors exhibit rational behaviour, ii) there is symmetric information, and iii) there are not market cost. However, these assumptions of the efficient market hypothesis have been widely challenged and criticized (Burton G, 2003).

1.2 Problem Formulation

Behavioural finance emerges as an alternative approach to incorporate in the study of financial decisions the investor's behaviour. The premise is that investment decisions are not always made based on full rationality, and this may be because people may make predictable, non-optimal choices when faced with difficult and uncertain decisions exhibiting heuristics and biases in their decisions (Subash, 2012). In fact, the research line of behavioural finance is based on an extensive collection of evidence pointing to the ineffectiveness of human decision making in various circumstances of economic decision making (Pompian, 2006).

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 judgments, and particularly regarding financial decisions, it could lead to serious disasters (Goodwin & Wright, 2014).

Portfolio theory, specifically concentrates on the nonlinear interrelationships between micro units to build an integrated portfolio, however, simply portfolios are not a linear sum of the parts. As mentioned, rationality assumption has been widely challenged, and new approaches attempting to study such assumption are emerging. Nawrocki & Viole (2014) believe that one would generate a better understanding of the financial markets behaviour if one does not strictly consider the rationality assumption. And attempting to do so, behavioural finance highlights as a relatively new paradigm in finance dealing with such challenge. In fact, behavioural finance aims to supplement the standard theories of finance by considering behavioural aspects of the investors in their financial decision-making process.

I agree that rationality is a strong assumption for attempting to explain portfolio theory and lately behavioural finance argues that investment decisions are not always made based on full rationality considering the existence of heuristics and biases affecting decisions of the investors.

1.3 Relevance

Most of the ineffectiveness of human decisions have been explained on the theory of biases or systematic errors in judgment (Chen et al, 2007). Tversky & Kahneman (1974) described three heuristics that are employed in making judgments under uncertainty: (i) representativeness, which is usually employed when people are asked to judge the probability that an object or event belongs to a class or process; (ii) availability of instances or scenarios, which is often employed when people are asked to assess the frequency of a class or the plausibility of a particular development; and (iii) adjustment from an anchor, which is usually employed in numerical prediction when a relevant value is available. These heuristics are highly economical and usually effective, but they may lead to systematic and predictable errors. And literature suggests that a better understanding of these heuristics and the biases could improve judgments and decisions in situations of uncertainty.

There is wide research about specific biases affecting the behaviour of investors. There are nine most common types of biases: i) overconfidence, ii) representativeness, iii) retrospective distortion, iv) anchor, v) cognitive dissonance, vi) aversion to repentance, vii) gambler's fallacy, viii) mental accounting, and ix) grazing. This research, focuses in studying overconfidence bias.

The relevant question is how to identify the presence of overconfidence and previous studies aimed to understand it, have mostly been undertaken by using questionnaires for extrapolating results as a measure of overconfidence, however the challenge is still to find a plausible measure that is valid. As Fama (2012) states: “Behaviourists are very good at storytelling and describing individual behaviour, however their jumps from individuals to markets are not validated by the data”.

Interestingly, studies about overconfidence are mostly undertaken from a static perspective, however given the nature in which a stock market operates, it would be desirable to research overconfidence from a dynamic perspective. This research has the following research questions: i) are stock market investors overconfident, and ii) if so, what are the dynamic mechanisms behind it.

1.4 Thesis Set Up

This thesis is organized as follows. In chapter two present the theoretical framework in which I discuss the efficient market hypothesis as the root of portfolio theory. I also present a brief introduction to behavioural finance as an attempt to incorporate behavioural aspects in finance theory, this motivated by the possible presence of heuristics and biases in the decision-making process of investors. I present the most common heuristics and their underlying biases and finally in this chapter the research questions and hypotheses are stated.

Chapter three presents the methodology section which focuses on the use of micro worlds as a tool which allows to conduct temporary monitoring of participants behaviour while investing in an artificial stock market setting and this generates data to create a proxy variable for studying the possible presence of overconfidence. Another method used is system dynamics modelling as a simulation tool that allows to quantify a dynamic model to test the hypothesis of this research. A description of the micro world developed is presented and its link to a simulation model is also shown. In chapter four, the results and discussion of the experiment and the simulation model are presented and Finally, in chapter five I present the conclusions, limitations and future research of this study.

2. THEORETICAL FRAMEWORK

In this chapter, I present the efficient market hypothesis and rationality grounds in which portfolio theory framework is built upon. I then introduce behavioural finance as a new approach incorporating behavioural aspects in the decision making of portfolio composition. I justify the aims of behavioural finance by introducing prospect theory and discussing about heuristics and the biases. At the end of this chapter I present the gap identified from this literature review and I propose the research questions and hypothesis.

2.1 Efficient Market Hypothesis

An ideal market is one in which prices provide accurate signals for resource allocation, which implies that this is a market in which investors can choose among the securities that represent ownership of firms' activities under the assumption that security prices at any time are fully reflecting all available information. If so, such market is an efficient market (Fama, 1970).

An efficient market is then, the market where rational agents meet to maximize their profit in a competitive environment. Each of these agents try to predict future market values of individual financial products, and current information is important as well as almost freely available to all participants. Fama (1970) stated that in an efficient market at any point in time, the actual price of a financial product will be a good estimate of its intrinsic value. In fact, efficient market hypothesis bases its grounds on three key assumptions: i) investors are rational, ii) in case some investors are irrational, their trades are random and cancel each other out without affecting prices, and iii) rational arbitrageurs eliminate the influence of irrational investors on market.

Understanding the concept of rationality is key for this research. Elbanna (2006) defines rationality in decision making as the reason for doing something and to judge a behaviour as reasonable, being able to say that the behaviour is understandable within a given frame of reference. This implies that rationality characterizes a behaviour which is logical in pursuing goals. However, rationality has been widely criticized for its lack of both empirical testing and validity (Buskens, 2015).

Undoubtedly, research has shown that some market participants are demonstrably less than rational. Thus, pricing irregularities and predictable patterns in stock returns can appear over time and even persist for short periods (Burton G, 2003). Therefore, the market cannot be perfectly efficient, if it was, one could say that there would be no incentive for professionals to uncover the information that gets so quickly reflected in market prices, a point stressed by Grossman and Stiglitz (1980). These authors have argued that because information is costly, prices cannot perfectly reflect the information which is available, since if it did, those who spent resources to obtain it, would receive no compensation, implying that there is a fundamental conflict between the efficiency with which markets spread information and the incentives to acquire information.

2.2 Portfolio Theory

A financial portfolio can be defined as the allocation of wealth among different available investments. Portfolio theory developed by Markowitz (1952), states that the process of selecting a portfolio may be divided into two stages. i) The first stage starts with observation and experience and ends with beliefs about the future performances of available financial products, and ii) the second stage starts with the relevant beliefs about future performances and ends with the choice of portfolio. Markowitz's article is concerned with the second stage. And his work states that one rule concerning choice of portfolio is that the investor is rational and maximizes the discounted value of future returns.

Markowitz stipulates that under certain conditions any investor can build an optimal risky portfolio by considering asset specific return (μ) and risk (σ), i.e. average return and standard deviation or volatility as the two essential factors. However, the resulting portfolio's risk is not merely the sum of each assets' risk, as the riskiness of the portfolio is not only dependent on the riskiness of the individual assets it is composed of, but also depends on the correlation of these assets. Despite criticism mainly focusing on the model oversimplifying reality through some of its assumptions (e.g. normally distributed returns, efficient markets), the model is still being taught in business schools (Gasser et al, 2017).

This traditional approach for composing optimal portfolios highly relies in the assumption that the agents are rational. Nawrocki & Viole (2014) consider that if one attempts to relax this assumption, this would generate a better understanding of the financial markets behaviour. However, I consider that relaxing the assumption is not the issue, the point is whether the rationality assumption has empirical validity or not. And farther more, in case there is not rational decision making at all, what are the implications of such deviations of rational decision making and its effect for the stock market.

2.3 Behavioural Finance

There is vast literature in criticizing the efficient market hypothesis and rationality assumption. Shleifer (2000) assesses the idea of efficient financial markets, evaluating the theoretical and empirical foundations of the efficient markets hypothesis. Shleifer emphasises how some of foundations of the EMH are contradicted by psychological and institutional evidence and special attention is given to the rationality of investors, the randomness of the trades, and the role of arbitrageurs. The author suggests that an alternative theory named behavioural finance could be more successful in explaining such evidence.

Modern financial economics assume that people behave with extreme rationality, but in fact they do not. Furthermore, people’s deviations from rationality are often systematic and behavioural finance relaxes this traditional assumption of financial economics by incorporating observable, systematic, and very human departures of rationality into standard models of financial markets (Barber & Odean, 1999).

Sewell (2010) defines behavioural finance as the study of the influence of psychology on the behaviour of financial practitioners and the subsequent effect on markets and it is of interest because it helps explaining why and how markets might be inefficient. Behavioural finance deals with theories and experiments focused on what happens when investors make decisions based or mixed with emotions.

Behavioural finance also deals with investors’ psychology while making financial decisions. It applies scientific research on human and social cognitive and emotional biases to better understand economic decisions and how they 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 use of emotions in financial decision-making (Chandra, 2008).

The decision making by individual investors is usually studied based on their age, education, income, investment portfolio, and other demographic factors. However, the impact of behavioural aspect of investing is often ignored. Chandra (2008) presents a vast literature review to explore the impact of behavioural factors and investor's psychology on their decision making, and examines the relationship between investor's attitude towards risk and behavioural decision making. The finds state that unlike the classical finance theory suggests, individual investors do not always make rational investment decisions. Their investment decisions are influenced to a great extent by behavioural factors like greed and fear, cognitive dissonance, mental accounting, and anchoring. And these behavioural factors must be considered when attempting to better understand the markets.

2.4 Heuristics and Biases

Studies on heuristics and biases have been proposed by Tversky, A. & D. Kahneman (1974). The authors state that people rely on a limited number of heuristics reducing the complex tasks of assessing probabilities and predicting values to simpler judgmental operations. In 1979, Tversky, A. & D. Kahneman presented a formal critique of expected utility theory as a descriptive model of decision making under risk, and proposed prospect theory. Choices among risky prospects exhibit several pervasive effects that are inconsistent with the basic tenets of utility theory, in particular, people underweight outcomes that are merely probable in comparison with outcomes that are obtained with certainty (Kehneman & Tversky, 1979).

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 judgments, and particularly regarding financial decisions, it could lead to serious loses (Goodwin & Wright, 2014).

Barber & Odean (1999) highlight two common mistakes investors make: i) excessive trading, and ii) the tendency to disproportionately hold on to losing investments while selling winners which means those exhibiting the highest returns. They argue that these systematic biases have their origins in human psychology.

One can say that heuristics are then simple efficient rules of the thumb which have been proposed to explain how people make decisions, come to judgments and solve problems, typically when facing complex problems or incomplete information (Parikh, 2011).

Studying portfolio investments should take into consideration heuristics and biases because of the high volume of financial products and their underlying information may trigger such mental rules. This suggests that investors may be tempted to use heuristics to allow them speed up their decision-making process which may not directly be related to a rational portfolio allocation. Researchers distinguish a long list of specific biases associated to heuristics (Subash, 2012). The following subsections present definitions for each heuristic and its underlying main biases.

2.4.1 Representativeness

Representativeness is an assessment of the degree of correspondence between a sample and a population, an instance and a category, an act and an actor or, more generally, between an outcome and a model (Gilovich et al, 2002). Many of the probabilistic questions with which people are concerned belong to one of the type: What is the probability that object A belongs to class B? and it is in answering such questions when people typically rely on the representativeness heuristic (Tversky & Kahneman, 1983). The following table describes the biases associated to this heuristic.

Table 1:
Biases related to representativeness heuristic

Bias	Description
Insensitivity to prior probability of outcomes	One of the factors that have no effect on representativeness but should have a major effect on probability is the prior probability, or base rate frequency of the outcomes. In fact, people evaluating probability by representativeness, neglects prior probabilities.

Bias	Description
Insensitivity to sample size	This bias implies to evaluate the probability of obtaining a particular result in a sample drawn from a specified population. That is, people assess the likelihood of a sample result, and the similarity of a sample statistic to a population parameter does not depend on the size of the sample.
Misconceptions of chance	People expect that a sequence of events generated by a random process will represent the essential characteristics of that process even when the sequence is short.
Insensitivity to predictability	People are sometimes called upon to make such numerical predictions as the future value of a stock, the demand for a commodity, or the outcome of a football game. Such predictions are often made by representativeness.
The illusion of validity	People often predict by selecting the outcome that is most representative of the input. The confidence they have in their prediction depends primarily on the degree of representativeness, that is, on the quality of the match between the selected outcome and the input with little or no regard for the factors that limit predictive accuracy.

Source: Tversky & Kahneman (1974)

2.4.2 Availability

There are situations in which people assess the frequency of a class or the probability of an event by the ease with which instances or occurrences can be recalled. For example, one may assess the risk of heart attack among middle-aged people by recalling such occurrences among one's acquaintances (Tversky & Kahneman, 1974). The following table describes the biases associated to this heuristic.

Table 2:
Biases related to availability heuristic

Bias	Description
Retrievability of instances.	When the size of a class is judged by the availability of its instances, a class whose instances are easily retrieved will appear more

Bias	Description
	numerous than a class of equal frequency whose instances are less retrievable.
Imaginability	Sometimes one must assess the frequency of a class whose instances are not stored in memory but can be generated according to a given rule. In such situations, one typically generates several instances and evaluates frequency or probability by the ease with which the relevant instances can be constructed.
Illusory correlation	An illusory correlation is the perception of a relationship between two variables when in reality, such relationship does not exist. When individuals believe that a relationship exists, they are more likely to notice their joint occurrence and, conversely, are less likely to remember the many times when there is no coincidence of events (Chapman, 1967).

Source: Tversky & Kahneman (1974)

2.4.3 Adjustment and Anchoring

In many situations, people make estimates by starting from an initial value that is adjusted to yield the final answer. The initial value, or starting point, may be suggested by the formulation of the problem, or it may be the result of a partial computation (Tversky & Kahneman, 1974). The following table describes the biases associated to this heuristic.

Table 3:
Biases related to adjustment and anchoring heuristic

Bias	Description
Insufficient adjustment	Anchoring occurs not only when the starting point is given to the subject, but also when the subject bases his/her estimate on the result of some incomplete computation.
Mislead evaluation of conjunctive and disjunctive events	Studies of choice among gambles and of judgments of probability indicate that people tend to overestimate the probability of conjunctive events and to underestimate the probability of disjunctive events. The stated probability of the elementary event (success at any one stage) provides a natural starting point for the estimation of the probabilities of both conjunctive and disjunctive events. Since adjustment from the starting point is typically

Bias	Description
	insufficient, the final estimates remain too close to the probabilities of the elementary events in both cases.
Assessment of subjective probability distributions	In decision analysis, experts are often required to express their beliefs about a quantity, such as the value of the Dow-Jones average on a particular day, in the form of a probability distribution. Such a distribution is usually constructed by asking the person to select values of the quantity that correspond to specified percentiles of his subjective probability distribution.
Overconfidence	Overconfidence is an unwarranted faith in one's intuitive reasoning, judgments, and cognitive abilities (Pompian, 2006).

Source: Tversky & Kahneman (1974)

For the purpose of this research, I focus in overconfidence bias related to adjustment and anchoring heuristic. There is vast literature to build upon, and studies have been conducted applied to decision in a financial market setting however there is room for contribution in terms of understanding the underlying feedback effects or mechanisms behind it. In the next section, I elaborate more about this bias and its measurement throughout relevant literature.

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

In the particular case of financial markets, a common trait among investors is a general overconfidence of their own ability when it comes to picking stocks, and to decide when to enter or exit a position (Subash, 2012).

These tendencies were researched by Barber & Odean (1999) who found that traders that conducted the most transactions tended, on average, to receive significantly lower yields. Furthermore, psychologists have determined that overconfidence causes people to overestimate their knowledge, underestimate risks, and exaggerate their ability to control events. And portfolio composition is a highly difficult undertaking and interestingly type of activity and it is precisely the task at which people exhibit the greatest overconfidence (Baker, Nofsinger, & John, 2002).

There are different types of overconfidence in the literature. Bar-Yosef & Venezia (2014) present three main types of overconfidence. The first type is overprecision or calibration of probabilities. As defined by Alpert and Raiffa (1982), 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.

A second type of overconfidence is overestimation or optimism. Researchers find that people overestimate their ability to do well on tasks (Frank, 1935), they are unrealistically optimistic about future events, they expect good things to happen to them more often than to their peers (Weinstein, 1980, Kunda 1987), and they are even unrealistically optimistic about pure chance events.

The above is linked to the third type of overconfidence that may be called better than the average or overplacement. Most individuals see themselves as better than the average person and most individuals see themselves better than others see them (Taylor & Brown, 1988). People rate their abilities and their prospects higher than those of their peers. Both overestimation and overplacement refer to an inclination to overestimate performance (e.g. the number of correct answers a person gives in a quiz) either in comparison with the actual performance or in comparison with the performance of others (Pikulina et al, 2017).

In this research, I focus in studying overestimation of investors in the stock market. One could think that the environment in which a stock market operates may influence investors tendency towards optimistic and overestimated behaviour about the upcoming performance of their transactions. However, the interesting question is how to measure the presence of overconfidence and more particularly overestimation in the investment decisions in a stock market setting.

2.5.1 Measuring Overconfidence

In recent years and in the context of financial decision, overconfidence has been measured by excessive trading. Barber & Odean (2000) 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 & Venezia, 2014).

However, theoretical models are still used to predict that overconfident investors will trade more than rational investors. Glaser & Weber (2007) directly test this hypothesis by correlating individual overconfidence scores with several measures of trading volume of individual investors. Approximately 3,000 online broker investors were asked to answer an internet questionnaire which was designed to measure various types of overconfidence (miscalibration, volatility estimates, better than average effect). The measures of trading volume were calculated by the trades of 215 individual investors who answered the questionnaire. The authors found that in fact, investors who think that they are above average in terms of investment skills or past performance (but who did not have above average performance in the past) trade more.

The traditional measure of overconfidence is the construction of intervals of confidence. This implies that in a typical experiment setting, subjects answer several binary choice general knowledge questions. For each question, subjects must choose which of the two suggested answers is correct in their opinion. Subjects are also asked to indicate their confidence on a 50%-100% scale that their answer is correct. Individual responses are then sorted by the revealed confidence level and the percentage of correct answers in each confidence category is calculated. Subjects are classified as overconfident if their stated confidence judgments are greater than the corresponding percentage of correctly answered questions (Blavatskyy, 2009).

Intervals of confidence require the decision makers to provide lower and upper bound estimates (intervals) for a set of questions like "How long is the Nile river?". Subjects are instructed to state intervals such that their own confidence is between these stated bounds, equals a confidence level that is requested by the experimenter, for example 90% (Langnickela & Zeisbergerb, 2016). On average, the ratio of true values that fall into decision makers' interval estimates (*hit rate*), should correspond to the requested confidence level (in this case 90%). However, commonly people are found to have much lower hit rates, so that they are classified as overconfident (Alpert & Raiffa, 1982) (Russo & Schoemaker, 1992).

In order to test overconfidence, Bar-Yosef & Venezia (2014) asked a sample of subjects to give 95% confidence intervals for a given set of variables to be forecasted. Then, the authors calculated the number of intervals that covered the true values. Since 95% confidence intervals are supposed to cover the true values in 95% of the cases, then, if the provided intervals cover the true values in less than 95% of the cases this may be a sign of overconfidence (Alpert & Raiffa, 1982).

Biais et al (2005) measure the degree of overconfidence in judgement in the form of miscalibration, i.e. the tendency to overestimate the precision of one's information and self-monitoring of 245 participants, observing their behaviour in an experimental financial market under asymmetric information. Miscalibrated traders, underestimating the conditional uncertainty about the asset value, were expected to be especially vulnerable to the winner's curse, while high self-monitors were expected to behave strategically and achieve superior results. Their basic analysis focuses on the direct link between psychological characteristics of the participants and their trading profits. To assess causal relations between independent variables (e.g. miscalibration, self-monitoring) and dependent variables (e.g. trading strategies, earnings) the authors use a quasi-experimental design. In line with Russo and Schoemaker (1992) and Klayman et al. (1999), the authors used confidence interval technique to measure miscalibration.

Alti & Telock (2014) structurally estimate a model in which agents' information processing biases can cause predictability in firms' asset returns and investment inefficiencies. They generalize the neoclassical investment model by allowing for two biases overconfidence and overextrapolation of trends that distort agents' expectations of firm productivity. Biases were estimated using direct measures of expectations from surveys and professional forecasts, more particularly, they measure overconfidence by the miscalibration of the declared confidence intervals of the agents.

Gleser et al (2013) extensively analyse interval estimates for knowledge questions, for real financial time series, and for artificially generated charts. They thereby suggest a new method to measure overconfidence in interval estimates, which is based on the implied probability mass behind a stated prediction interval. The authors performed a pre-experimental meeting in which they interviewed the subjects to better understand their decision scope and goals. In the first phase, a questionnaire was presented that asked for confidence intervals with respect to knowledge questions. In this phase, they also collected demographic data. The study consists of three tasks: i) Predictions of artificially generated charts via confidence intervals. ii) Confidence intervals for 20 knowledge questions (10 questions concerning general knowledge and 10 questions concerning economics and finance knowledge), and iii) stock market forecasts via confidence intervals.

Despite the vast applications of confidence intervals, recent studies have suggested that the interval measure may not function as presumed. It has been 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 & Jørgensen, 2005). Langnickela & Zeisbergerb (2016) confirm weaknesses of the interval measure presented in Teigen and Jorgensen (2005) and they show that decision makers not even adjust their frequency judgments to different levels of requested confidence. Using decision makers' frequency judgments, the authors find evidence that people respond to an individual confidence level that is unaffected by the requested confidence level.

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 (Lichtenstein & Fischhoff, 1977). However, Juslin et al. (2000) conducted a meta-analysis of seventeen previous studies and found that the hard/easy effect is nearly eliminated when researchers carefully control for the scale end effects (the upper and the lower bound on confidence scores) and linear dependency.

Gigerenzer et al (1991) argue that when estimating overconfidence through confidence intervals, subjects appear overconfident because an experimenter often selects non-representative general knowledge questions for which commonly used cues are not particularly useful. The authors find that observed overconfidence is significantly reduced if a representative set of general knowledge questions is used in the experiment.

In sum, in a typical setting, subjects are asked to reveal a lower and upper bound for the n-percent confidence interval of a correct answer to a general knowledge question, a future price in the experimental market, a ranking of their ability level etc. Subjects are classified as overconfident if a variable of interest falls into the stated interval in less than n percent. Despite the popularity of the method, elicitation of confidence intervals is not incentive compatible. If subjects are not informed about the exact mechanism how they earn money before they state their confidence intervals, there is no financial incentive for revealing subjective confidence intervals of cases (Blavatskyy, 2009).

Fagerström (2008) conducted a study to investigate overconfidence and overestimation in the stock market and factors that affect human beings in decision making when it comes to investing and analysing. The author performed a quantitative back testing exercise method based on historic data taken from Institutional Brokers' Estimate System IBES. Results showed that analysts of the Standards and Poor's S&P 500 were exaggerated by the problems of over confidence and the over optimistic biases.

Chuang & Lee (2006) developed an empirical evaluation of overconfidence because the existing models to test overconfidence exhibit anomalous findings, including a short-term continuation and a long-term reversal effect in stock returns. The authors propose four overconfidence hypotheses: First, if investors are overconfident, they overreact to private information and underreact to public information. Second, market gains make overconfident investors trade more aggressively in subsequent periods. Third, excessive trading of overconfident investors in securities markets contributes to the observed excessive volatility. Fourth, overconfident investors underestimate risk and trade more in riskier securities. To document the presence of overconfidence in financial markets, they empirically evaluate these four hypotheses using aggregate data consisting of all firms listed on the New York Stock Exchange- NYSE during the period January 1963 to December 2001 with the restriction that firms have been listed for at least 4 years. The findings are that overall, there is empirical evidence in support of the four hypotheses.

It seems a common trend that theoretical models predict that overconfident investors trade excessively. Barber & Odean (2001) test this prediction by partitioning investors on gender. Their research demonstrates that, in areas such as finance, men are more overconfident than women. Thus, evidence reflects that men trade more excessively than women. Using account data for over 35,000 households from a large discount brokerage, the study analyses the common stock investments of men and women from February 1991 through January 1997. The authors document that men trade 45 percent more than women and trading reduces men's net returns by 2.65 percentage points a year as opposed to 1.72 percentage points for women.

Grinblatt & Keloharju (2009) analyse the role that sensation seeking and overconfidence, play in the tendency of investors to trade stocks. They combine equity trading data from Finland with data from investor tax filings, driving records, and mandatory psychological profiles. The authors use these data obtained from a large population to construct measures of overconfidence and sensation seeking tendencies. Interestingly, the authors consider that to assess whether overconfidence explains trading, it would be useful to directly observe a measure of overconfidence, rather than a measure that is tied to a characteristic of the investor for example gender based instrument.

Ho (2011) examines the influence of overconfidence and the disposition effect from the accounts of individual investors in the Taiwanese market. The article aims to investigate the relationships among psychological biases, private information, trading strategies, and irrational behaviour of investors. The author states that previous studies of these phenomena have used five proxy variables: i) the turnover rate, ii) the degree of possession of private information, iii) dealing on credit, iv) the disposition coefficient, and v) the return on investment. For the case of measuring overconfidence, given that it is the most frequently psychological bias mentioned in behavioural finance, the author studies the turnover rate as a proxy variable. When investors are overconfident, they will trade excessively and, hence, raise their turnover rates (Odean, 1998; Barber and Odean, 2000; Statman et al., 2006). Investors with high turnover rates are then overconfident (Glaser & Weber, 2003).

The stock turnover rate seems a suitable proxy variable for measuring overconfidence. However, as ones deepens into the rationale behind it, limitations can be easily perceived. Consider the following table presenting transactions for three investors $i = A, B, C$ acquiring shares during $t = 1, \ldots 9$ periods.

The following table also presents the turnover rate for each each period for each investor.

$$Turnover\ Rate_t^i = \frac{Transactions_t^i}{\sum_{t=1}^{9} Number\ of\ Shares} \tag{1}$$

Table 4:
Turnover rate calculation

Period	A	B	C	Turnover Rate A	Turnover Rate B	Turnover Rate C
1	10	90	3	0,11	1	1
2	10	0	0	0,11	0	0
3	10	0	0	0,11	0	0
4	10	0	0	0,11	0	0
5	10	0	0	0,11	0	0
6	10	0	0	0,11	0	0
7	10	0	0	0,11	0	0
8	10	0	0	0,11	0	0
9	10	0	0	0,11	0	0
Total	90	90	3			

Source: Ho (2011)

One can calculate the average turnover rate as a proxy of overconfidence, however following the example above, the average turnover rate would be 0,11 for each of the investors A, B, and C. If the average turnover rate is used to rank the overconfidence of investors, then investors A, B, and C are likely to be identified with the same characteristics and grouped together. However, investor B might possess certain information in a particular period, which would explain the large number and high concentration of his/her transactions. The type of information reflected in B's trades is likely different from that of investors A and C. Therefore, the above classification is prone to bias (Ho, 2011).

To cope with the problem stated above, Ho (2011) proposes to replace the average turnover rate with the actual average number of transactions, which is the total number of transactions divided by the actual number of months with transactions.

$$Actual\ Average\ Number\ of\ Transactions = \frac{\sum_{t=1}^{T} Number\ of\ Shares}{Number\ of\ active\ periods} \qquad (2)$$

This criterion is then used to rank and classify investors. For the example mentioned above, the actual average number of transactions is 10, 90 and 3 respectively for each investor. The samples are then divided into two groups based on the median. One of these groups consists of those investors with high actual average numbers of transactions; that is, overconfident investors. Therefore, 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).

Ideally, in a controlled experiment of whether overconfidence affects trading activity, all other attributes of the subjects would be identical and only overconfidence would vary. However, in a social science experiment, this ideal is not attainable, and the lack of empirical corroboration in the literature of a relation between overconfidence and investments can be explained by practical difficulties in distinguishing between confidence and actual ability. Without a proper reference point (a person's actual ability), it is impossible to identify whether that person overestimates or underestimates his/her skill in a specific domain (Pikulina et al, 2017).

For the case of studying overconfidence, confidence intervals highlight in the literature as a popular measure. However, this usual way of measuring overconfidence must be treated with caution (Glaser & Weber, 2007). The limitation for using intervals of confidence is that regardless the significance level we ask the participants, the hit rate will converge always to the same because participants do not adjust the width of their interval.

Now, regarding the use of average turnover rate, 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.

In this research, I use the actual average number of transactions proposed by Ho (2011) as a proxy for measuring overconfidence. And I stick to the premise that when investors are overconfident, they trade excessively and hence, raise their actual average number of transactions (Odean, 1998; Barber and Odean, 2000; Statman et al., 2006).

One can conclude that when it comes to the measurement of confidence in own knowledge with monetary incentives, the most popular method is arguably an elicitation of confidence intervals (Russo & Schoemaker, 1992). However, using proxy variables such as the actual average number of transactions are helpful and allow to characterize overconfidence of stock market investors.

2.6 Research Questions and Dynamic Hypothesis

Classical finance and the study of financial markets from a normative point of view have their foundations in the rationality of economic agents. The main hypothesis revolves around decision making under rationality which implies that any financial decision is taken as if an investor is maximizing a certain expected utility mostly named welfare. However, this assumption has been contradicted repeatedly through research within the field of behavioural finance which aims to specifically investigate irrationality in economic decision making. Moreover, there have also been theoretical studies proving that investors do not act as if they are rational, but on the contrary, they exhibit many biases that lead to poor investment decisions in specific contexts (Toma, 2015).

Portfolio theory addresses that investors are fully rational, information is symmetric and that there are not transactions costs. However, there is room for relaxing these assumptions and investigating behavioural aspects affecting portfolio composition

Much of the research discussed before in this thesis, seems to report patterns regarding the behaviour of financial market investors affected by overconfidence in terms of their excessive trading. However, there is little evidence of research attempting to understand the dynamics mechanisms behind overconfidence and its effects in the decisions of stock market investors. To do so, I propose the following two research questions:

> **RQ1:** Are decision makers in financial markets overconfident in their decision making?
>
> **RQ2:** If so, what are the dynamic mechanisms behind it?

Brehmer (1992) reviews research on dynamic decision making, i.e., decision making under conditions which require a series of decisions, where the decisions are not independent, where the state of the world changes, both autonomously and because of the decision maker's actions, and where the decisions must be made in real time. The author states that it is difficult to find useful normative theories for these kinds of decisions, and research thus must focus on descriptive issues. This is the case of decision making in a financial market, in which decisions are not independent and the wealth of the investor is subject to change by his/her decisions, however studying such dependency is not an easy task.

Dynamic decision-making research grew out of a perceived need for understanding how people control dynamic, complex, real world systems. Examples of routine dynamic decision-making tasks include choosing which routes to take while driving a car, developing and selecting the best strategy while playing basketball, or/and investing in the stock market while prices are changing.

Dynamic Hypothesis:

Here I propose a dynamic hypothesis regarding the desired number of shares (See Figure 1). The dynamic hypothesis is presented in a causal loop diagram (CLD) which is an important tool for representing the feedback structure of systems. Long used in academic work, and increasingly common in business, CLDs are excellent for quickly capturing hypotheses about the causes of dynamics, eliciting and capturing the mental models of individuals or teams, communicating the important feedbacks (Sterman J. , 2000).

The motivation for having a dynamic hypothesis is that previous research sticks to an static perspective, however it is interesting to understand the feedback effects that overconfidence plays in a stock market setting.

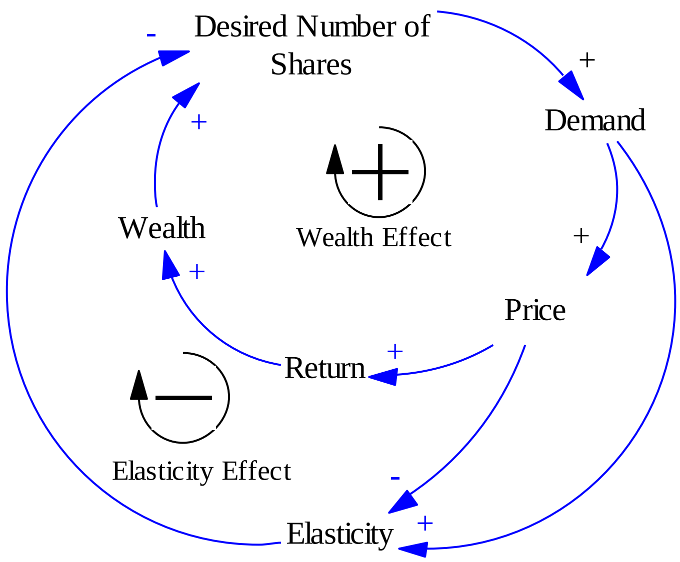


Figure 1: Causal Loop Diagram

The figure above exhibits two major loops that will serve to answers the research questions.

- **Wealth Effect:** The more the number of shares desired by the investor, the more the demand for the share. The more the demand, the higher the price. The higher the price the higher the returns. The higher the returns, the higher the wealth. The higher the wealth the higher the desired number of shares. This is a reinforcing loop.
- **Elasticity Effect:** The more the number of shares desired by the investor, the more the demand for the share. The demand affects the elasticity in terms on price and quantities. The more the demand, the higher the price, and the higher the price the

less the elasticity, however the more the demand the more the elasticity. And this elasticity is negatively related to the desired number of shares. This is a balancing loop.

H1: Overconfident investors exhibit lower elasticities[1] which explains their excessive trading

There are different models representing financial markets, i.e. Provenzano (2002) developed an artificial financial market in a system dynamics environment modelling the market's behaviour and characterizing asset's price and wealth dynamics arising from interactions of heterogeneous agents. The author models the investors' trading rules as the strategies used in the real world.

Sterman, J (2000) develops a model in which he considers the price setting process in a market such as a commodity or stock market. The demand for the good falls as prices rise; supply rises as price rises. In equilibrium price is just high enough to balance demand with supply. But how do the market makers (the people who set prices by calling out bids and offers in the trading pit) find the equilibrium price? And how do prices change when there is an imbalance between demand and supply? To answer such questions, the author presents a system dynamics model in which the price formation process forms two loops. Price adjusts to the indicated level, forming a negative price adjustment loop, but the indicated price is based on the current price, forming a positive price discovery loop. The responses of demand and supply to price form two additional negative loops.

In this research, I developed a system dynamics model that captures the dynamics discussed above in the hypothesis.

[1] Elasticity refers to the change in demand when prices change.

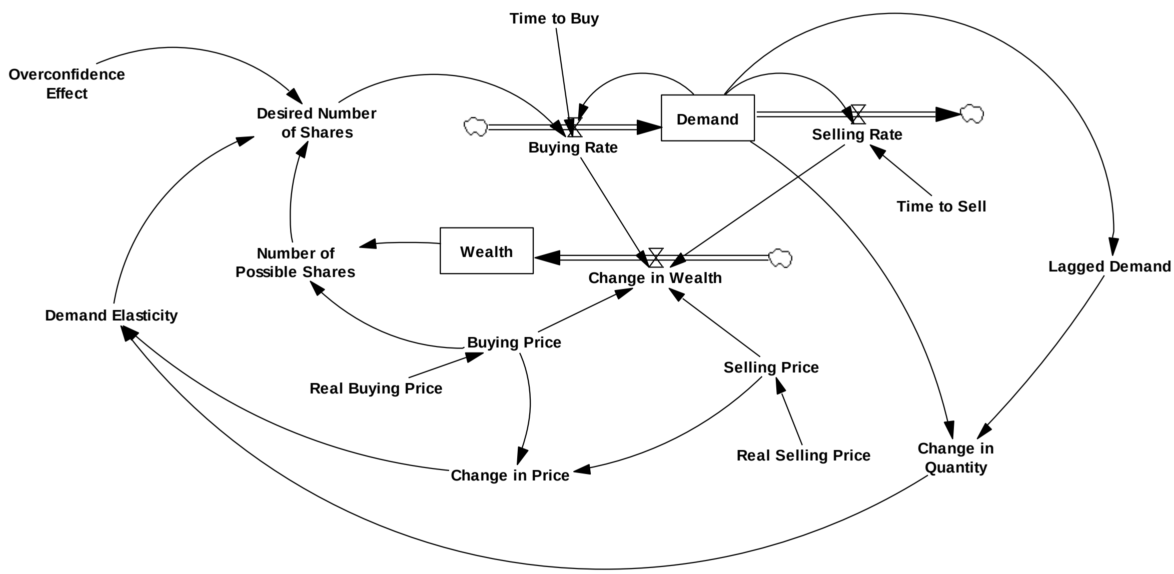


Figure 2: System Dynamics Model

In the following section, I present the methodology used in this research in order to answer the research questions and test the hypothesis mentioned above.

3. METHODOLOGY

In this section, I present the methodological framework for developing a micro world that allows to conduct this study This experiment allows to conduct temporary monitoring of the participants' preferences while generating data to create proxy variable that allows to study the presence of overconfidence when they compose their portfolios. Then I quantify a system dynamics model to study the dynamic effects of overconfidence in the stock market.

This section presents micro worlds as an experimental methodology. I present the characteristics of the micro world in terms of set up, the decision makers participating, the software used to develop the micro world, a look to the interface and a summary of the data collected with this experiment. Then I introduce the simulation as a second important method in this research.

3.1 Micro Worlds

Dynamic decision making has describable characteristics and with some unavoidable sacrifice of realism, is suitable for study in a laboratory setting using complex computer simulations commonly called micro worlds (Gonzalez et al, 2005). Morecroft (1988) and Senge (1990) developed a common methodological approach named 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.

Computer simulations play an integral role in dynamic decision-making research. Researchers refer to these simulations by various names, including micro worlds, synthetic task environments, high fidelity simulations, interactive learning environments, virtual environments, and scaled worlds, just to name a few (Gonzalez et al, 2005). I use the term micro worlds here because it appears to be the earliest term used to describe the complex simulations utilized in controlled experiments designed to study decision making as mentioned by Turkle (1984).

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). The assumption is that although microworlds are relatively simple, they embody the essential characteristics of real world.

By compromising the mundane realism often emphasized by naturalistic decision making, microworlds 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, microworlds have been hailed as tools that bridge the gap between laboratory and field research (Brehmer & Dörner, 1993).

3.2 Simulation

In the realms of simulation modelling, several approaches exist (Davis et al. 2007; Harrison et al. 2007). The commonly employed methodologies are discrete events, agent based, and system dynamics simulations. In this research, I have opted for system dynamics because of the continuous nature of a stock market (e.g., Morecroft and Sterman 1994; Sterman 2000; Sterman et al. 2007).

System dynamics is a methodology applied to dynamic problems arising in complex social, managerial, economic, or even ecological systems characterized by interdependence, mutual interaction, information feedback, and circular causality. It is a computer based approach to design and analyse policy decisions in any field, allowing researchers to empirically test and quantify the processes that underlie the dynamics the studied system (System Dynamics Society, 2017).

This methodology was conceived and developed in the late 1950's and early 1960's at the Massachusetts Institute of Technology by Jay Forrester. Its founder defines system dynamics as an approach for modelling and simulating complex physical and social systems and for experimenting with the models to design strategies for management and change (Forrester, 1961).

This modelling method serves to map structure, capturing and communicating an understanding of the behaviour driving processes and the quantification of the relationships to produce a set of equations that form the basis for simulating possible system behaviours over time. These models are powerful tools which help to understand and leverage the feedback interrelationships of complex systems (Cosenz, 2015).

Quite important to highlight, system dynamics principles state that models are based on a feedback view of the system, seen as a closed boundary, i.e. embodying all the main variables related to the phenomenon being investigated. It accounts for accumulations, nonlinearities, delayed cause and effect, and feedback relationships between variables which are the building blocks of dynamic complexity (Groesser, 2012).

Dynamic complexity is the reason why intuitive decisions often lead to unexpected results or to short term success and long-term failure (Senge 1990; Sterman 2000). System dynamics method enables decision makers to identify and assess the consequences of their actions in dynamic and complex situations from an integrated perspective.

This suggests that modelling a financial stock market calibrated with real data obtained from a micro world would allow to generate understanding about the dynamics of such system, and more important, one could try to understand the effects of overconfidence in the stock market.

I find important to highlight that studies on building theory with simulations suggest that there are very different ways of arriving at a theoretical contribution. De Gooyert (2016) provided a systematic review of system dynamics based theoretical contributions and the findings report that between 1990 and 2016, only 25 articles have provided a system dynamic based theoretical contribution in major management journals. The author concludes saying that perhaps system dynamics in management theory is still far from being a well-established research strategy. However, I consider that if researchers integrate system dynamics with other methods such I do in this study, more theoretical contributions will be generated from the field.

In summary, linking micro worlds and simulation, one can say that a micro world becomes a laboratory for testing hypotheses about the real world in controlled simulated environments. Subjects make choices in an experimentally controlled setting which provides information, as they are free to make any choice they consider appropriate, given the available operating information, knowledge, incentives, mental models, and cognitive limitations. Once the results have been generated, one can model and simulate the player's heuristics and compare them with the optimal decision rule to probe the link between expected results and observed dynamic behaviour (Morecroft J. , 1988).

I believe that as simulations are versatile, they can be relatively easily combined with other methods aiming to generate theoretical contributions. Reason why this research combines simulation and micro world approaches, to maintain the flexibility of the simulation and the insights generated in a micro world for validation with empirical data.

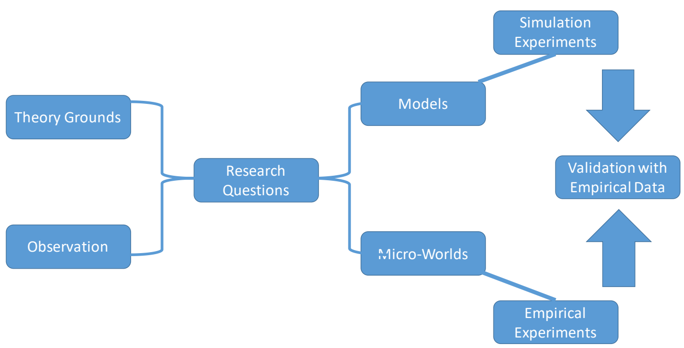


Figure 3: Theoretical Framework

Figure 4 presents the conceptual model underlying this research. I believe that given some outcomes of the investments, biases and heuristics are subject to appear and influence the portfolio investments. Depending on the outcome of the investments, the micro world setting will update the information provide to compose the portfolio.

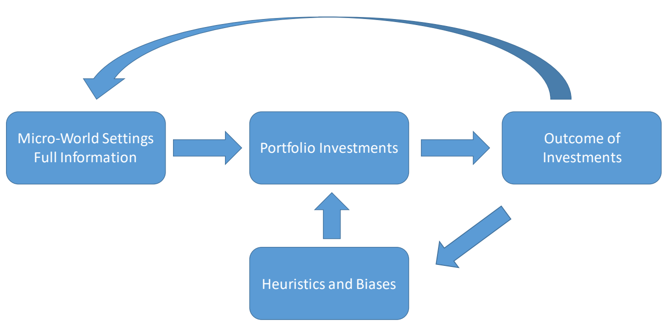


Figure 4: Conceptual Model

3.3 Micro World Characteristics

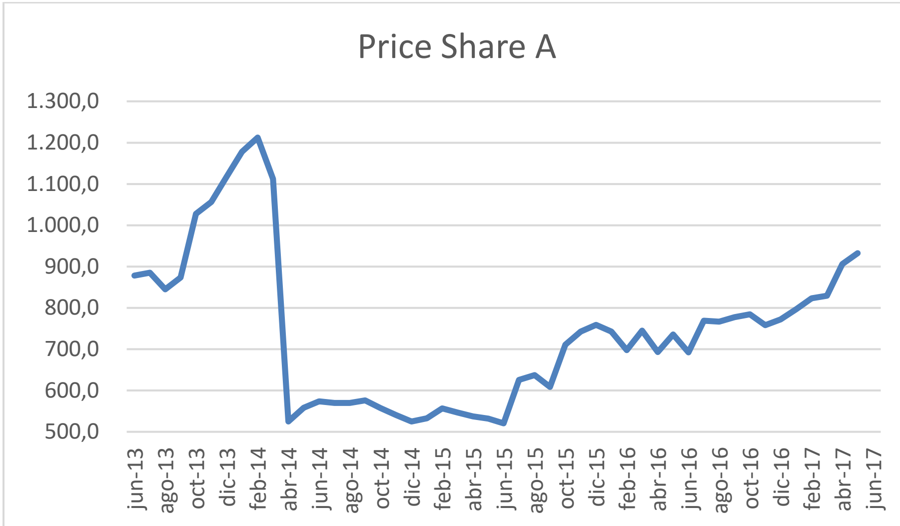
The micro world is representation of an artificial financial market with the following characteristics:

- There is capital market with $N = 2$ risky assets, each with random rates of return for each period r_t^n.
- The investor joins the market at time 1 with an initial wealth $W_0 = 10.000$ euros and the goal is to maximize this amount.
- 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 investor can allocate all or part of the wealth among the N assets.
- The wealth can be reallocated among the N 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 $r_t^n = [r_1^n, r_2^n, \dots., r_t^n]'$, where r_t^n is the random return for asset n at the time t.
- The time frame for the investments is $t = 13$.
- The time available for each decision is maximum two minutes[2].

Time series data was collected for two companies that will be named A and B. It's important to highlight that this is real information from the two big companies in the American stock market[3] and the information ranges from June 2013 to May 2017 (*See Figure 5 and 6*).

[2] For instructions for the experiment see Annex 1, and for the logbook of the experiment see Annex 2.

[3] The companies are Coca-Cola and Google. (Yahoo Finance, 2017)



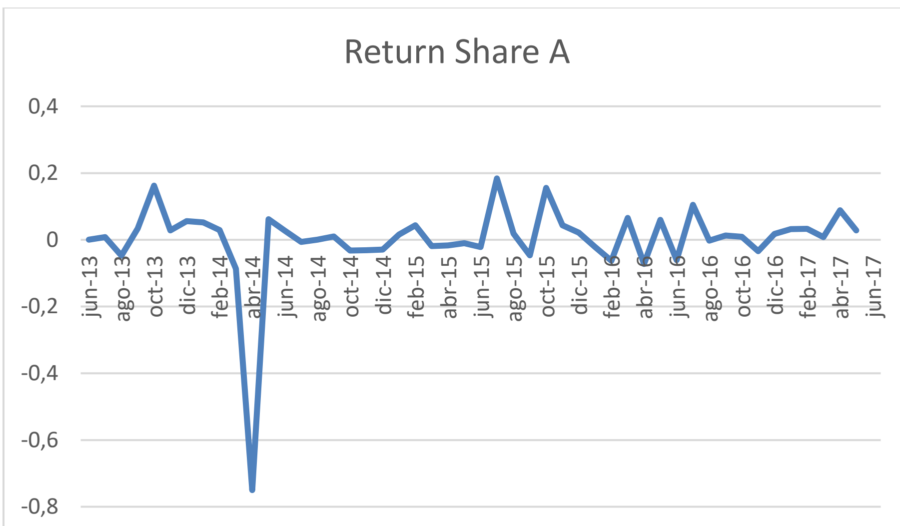
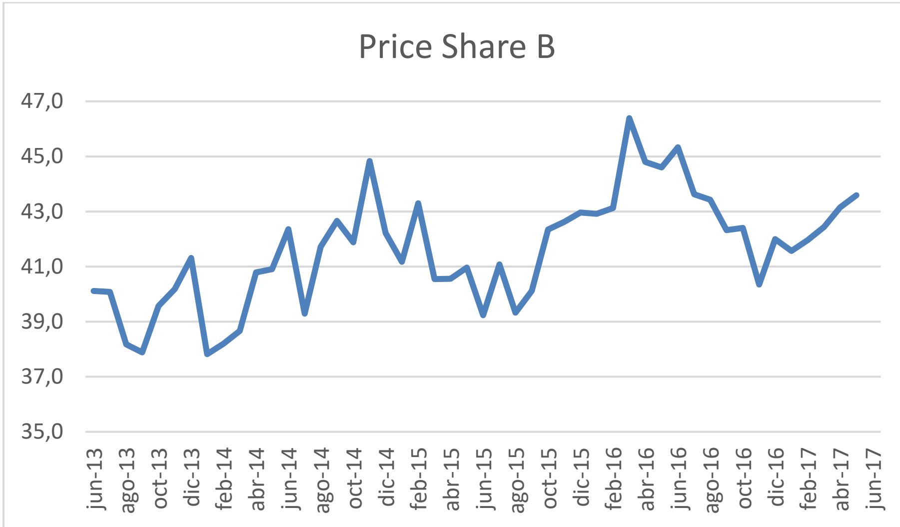


Figure 5: Historical Price Behaviour for Share A



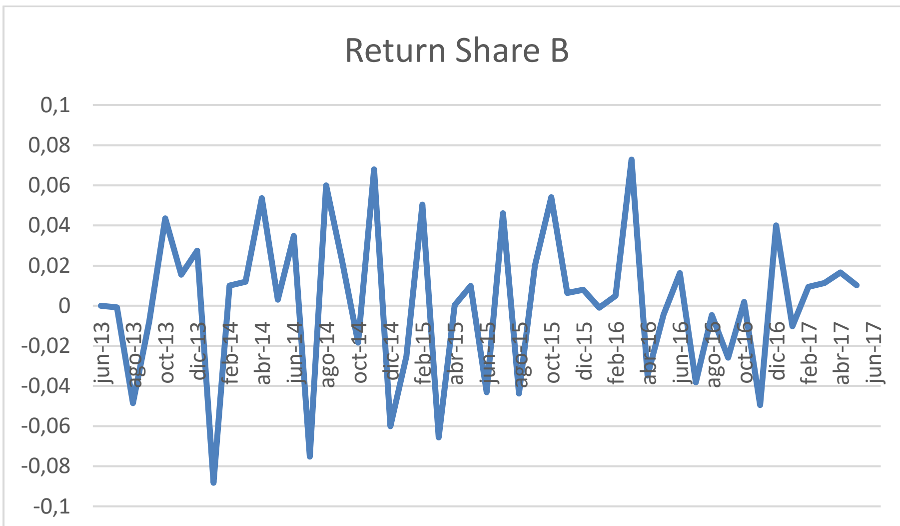


Figure 6: Historical Price Behaviour for Share B

The historical information exhibited above, was the first information presented to the participants and then they had to decide the quantity of shares to buy in case they wanted to buy. After the participant inserts the quantity of shares desired to buy, the next period starts and the profits or loses of the previous period are presented. In order to reduce complexity, this is not a simultaneous experiment, so I did an ARIMA pricing model that allows to forecast the price of both shares for the period June 2017 to June 2018 (See Annex 3).

3.3.1 Participants and Software

The participants of experiment were mainly Bachelor, Master, Ph.D., and Postdoc students. I managed to gather 77 participants of different latitudes of Latin America and Europe. The experiment was programmed and conducted with the experiment software Z-Tree (Fischbacher, 2007). Z-Tree, Zurich Toolbox for Readymade Economic Experiments is a software for developing and conducting economic experiments. The software is stable and allows programming almost any kind of experiments in a short time. It also enables to create a user-friendly representation of the financial market avoiding confusions to the participant.

3.3.2 Interface

The following is the interface the participant faces in the first period. On the left side, historic information is provided about the behaviour of the price and the return of each share. On the top right side, the price and the average return for each share is communicated to the participant. There is also information about the current wealth and the only decisions the participants can make is to decide what number of shares either A or B they want to buy in the market in case they want to buy (See Figure 7). Once they made their decision, the button ok shows the results for that period. The information is then updated for the following periods (See Figure 8).

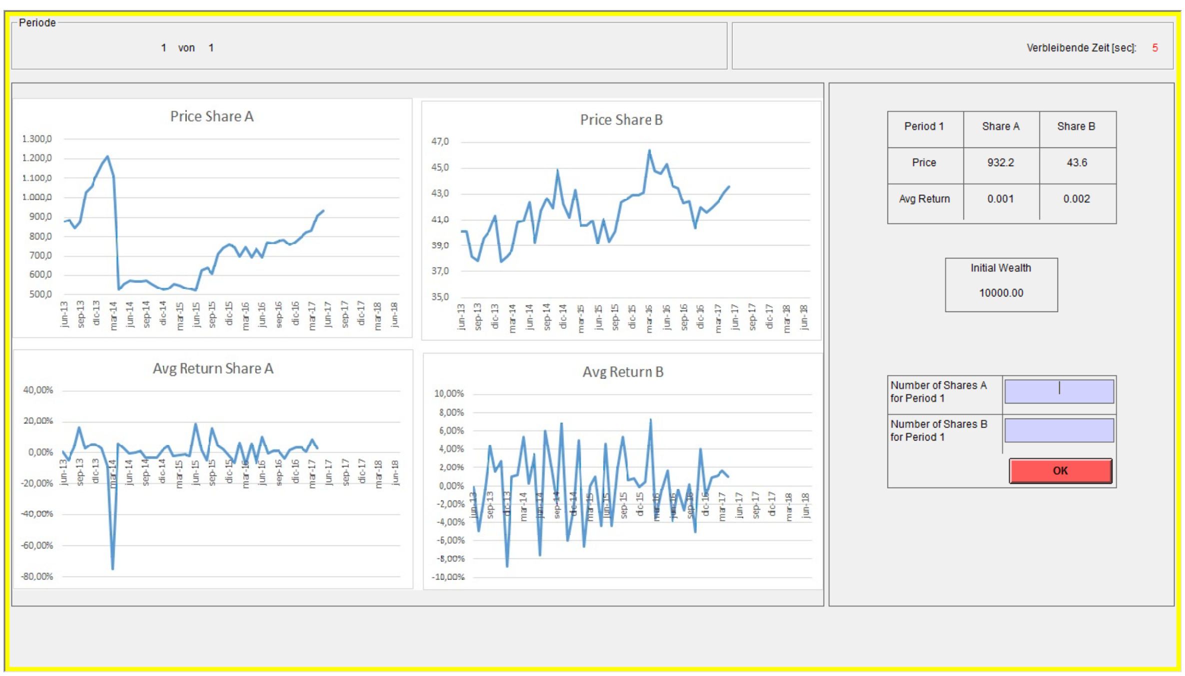


Figure 7: Interface Decision Page

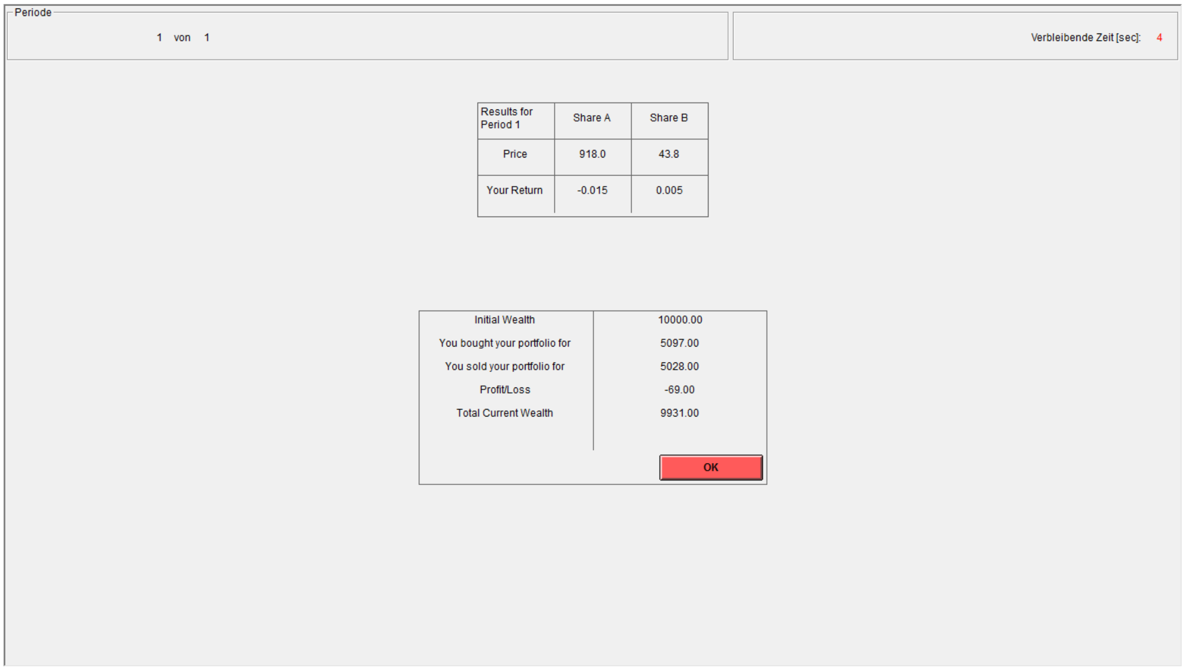


Figure 8: Interface Results Page

3.3.3 Data

The micro world allows to collect primary data about the decisions made by the participants in each of the rounds of the micro world. The following table mentions the data gathered.

Table 5:
Primary Data

Variable	Description
Shares acquired in each period $\boldsymbol{N_t^n}$ Where $\boldsymbol{n = 1, 2}$ and $\boldsymbol{t = 1, \ldots 13}$	Type and number of shares bought by the participant in each period.
Buying Price $\boldsymbol{BP_t^n}$ Where $\boldsymbol{n = 1, 2}$ and $\boldsymbol{t = 1, \ldots 13}$	Figures about the price in which the share was bought.
Selling Price $\boldsymbol{SP_t^n}$ Where $\boldsymbol{n = 1, 2}$ and $\boldsymbol{t = 1, \ldots 13}$	Figures about the price in which the share was sold.

Variable	Description
Return $$\boldsymbol{LN = \frac{SP_t^n}{BP_{t-1}^n}}$$ Where $\boldsymbol{n = 1, 2}$ and $\boldsymbol{t = 1, \ldots 13}$	Calculation on the earnings obtained for each share.
ROI $$\boldsymbol{ROI = \frac{Total\ Profit}{Initial\ Wealth}}$$	Return on investment
Cumulative Wealth $$\boldsymbol{\sum_{t=1}^{12} w_{t-1}^n (1 + r_t^n) + w_t}$$ Where $\boldsymbol{w_{t-1}^n}$refers to the investment made in share $\boldsymbol{n}$ in the $\boldsymbol{t-1}$ period for the same share.	Total accumulative amount of money earned in each period

An mentioned in chapter two, once this information was collected, I proceeded to calculate a measure of overconfidence. In this research, I use the actual average number of transactions proposed by Ho (2011) as a proxy for measuring overconfidence.

$$Actual\ Average\ Number\ of\ Transactions = \frac{\sum_{t=1}^{13} Number\ of\ Shares}{Number\ of\ active\ periods} \qquad (2)$$

This criterion is then used to rank and classify the overconfidence of investors. The sample is then divided into two groups based on the median. One of these groups consists of those investors with high actual average numbers of transactions; that is, overconfident investors (Ho, 2011).

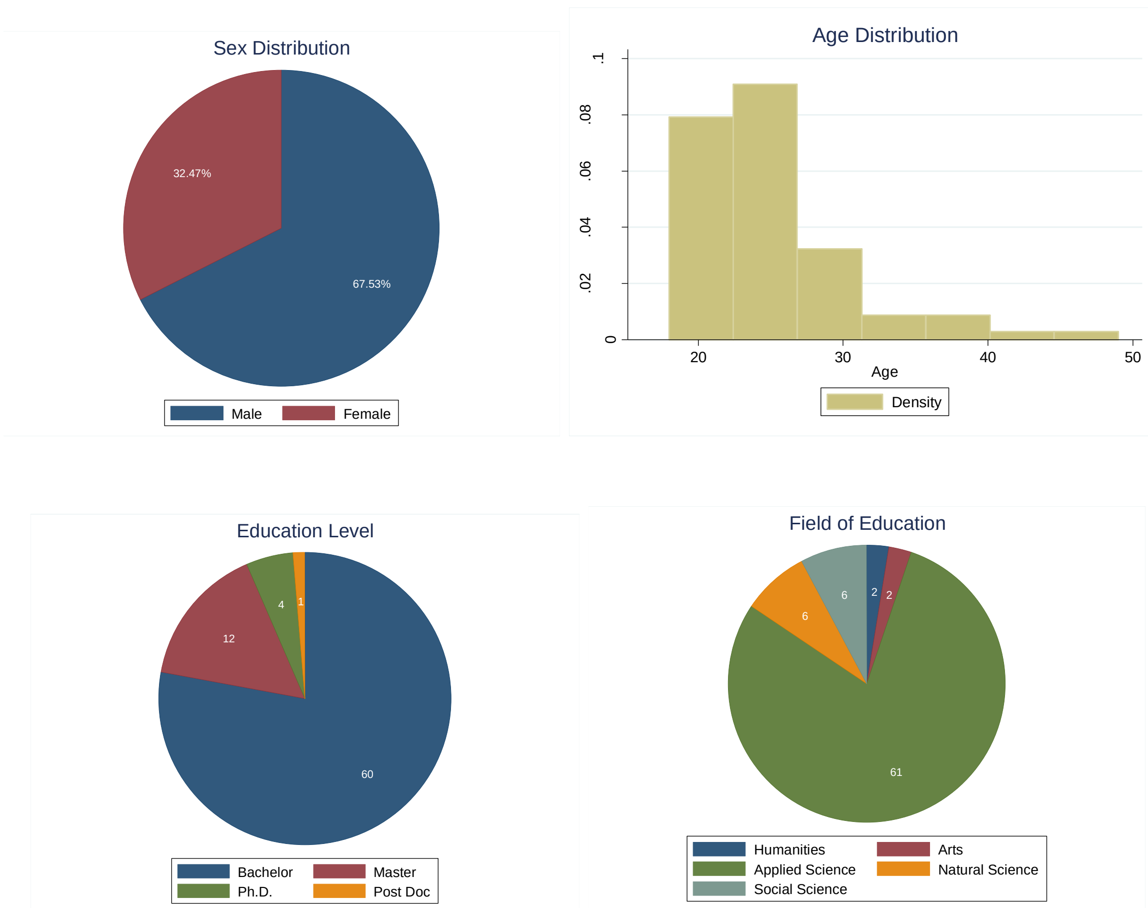
Once we have these two groups, statistics are generated to analyse how different both groups are. The elasticity for each group is calculated and it allows to test how both groups react to changes in prices and its effects on the demand of shares. I also look at the relationship of overconfidence and demographic variables such gender, level of education, age, nationality, and field of studies. This will be broadly presented in the chapter of results.

4. RESULTS AND DISCUSSION

In this chapter, I present the main results of this research. Descriptive statistics and econometric analysis are presented and the results of the simulation as well.

4.1 Descriptive Statistics

The experiment was conducted with 77 participants from which 67,53% were males and 32,47% were females. The distribution of the age is highly concentrated between 20 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 (*See Figure 9*).



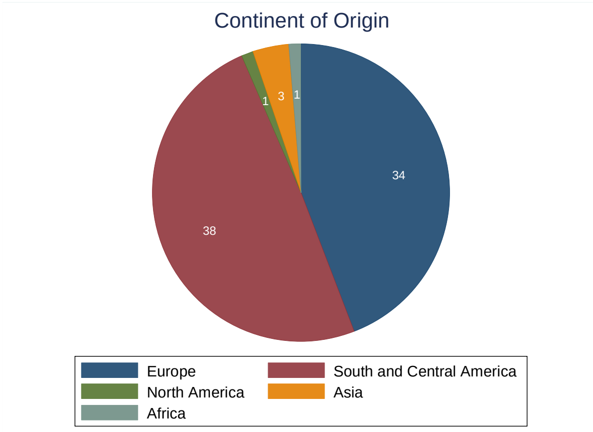


Figure 9: Characterization of the sample

To calculate the actual average number of transactions - AANT as a proxy for measuring overconfidence, I calculated one AANT for the shares type A, and another for shares type B, with these a scale of overconfidence is proposed. If an investor exhibits overconfidence for both types of shares this is classified as strong overconfidence, while if he/she only exhibits overconfidence for one of the shares then he/she classified as moderate overconfidence.

The following figures show that participants with hard levels of overconfidence, in average buy more shares, followed by the participants with moderate levels, and the more steady and lower number of shares are acquired by participants not exhibiting overconfidence at all (*See Figure 10*).

Figure 10: Average number of shares for each level of overconfidence

Interestingly and in line with what was mentioned in the literature review, participants exhibiting any degree of overconfidence, perceive either higher or lower returns compared with the participant without any overconfidence (*See Figure 11*).

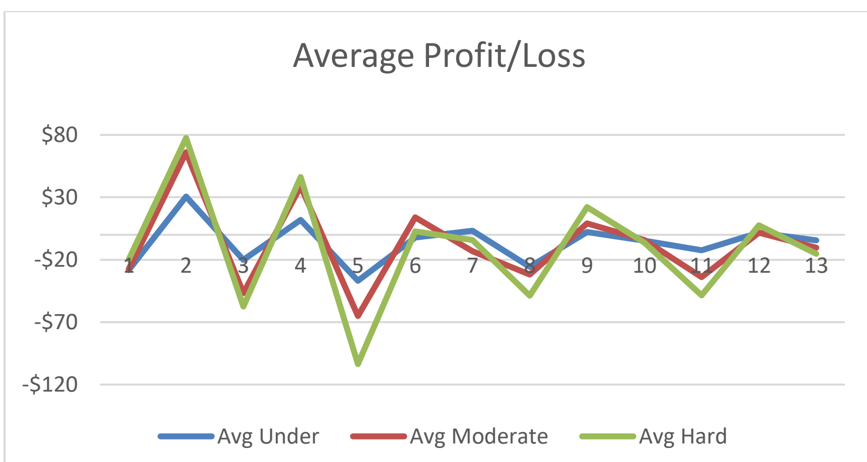


Figure 11: Average profit loss of the participants

From the total sample, 58 participants exhibited overconfidence behaviour. From those 45 were males, while just 13 were female. Regarding the degree of education, 44 overconfident investors held bachelors, while just 14 held a higher degree. In terms of the field of study, 48 of the overconfident investors belong to social science while 10 belong to another field. From the overconfident subsample, 26 are Europeans, and 28 are from Latin America, while just 4 come from another continent. And regarding the age, 36 overconfident participants are younger than 25 years old while 22 are older than 25.

Table 6:
Overconfidence characterization

	Underconfident	Overconfident	Total
Males	7	45	52
Females	12	13	25
Degree of Education			
Bachelor	16	44	60
Higher Degree	3	14	17
Field of Study			
Social Science	13	48	61
Another Field	6	10	16
Continent of Origin			
Europe	8	26	34
Latin America	10	28	38
Others	1	4	5
Age Group			
Younger than 25	14	36	50
Older than 25	5	22	27

4.2 Regression Analysis

To validate the significance of the results and to verify which variables explain the overconfidence of the participants, a logistic regression was performed.

$$Overconfidence_i = \beta_0 + \beta_1 Wealth_i + \beta_2 Gender_i + \beta_3 Age_i + \beta_4 Minor25_i$$

$$+\beta_5 European + \beta_6 Socials_i + \beta_7 Postgraduate_i + \varepsilon_i$$

$$Overconfidence_i = \begin{cases} 1, & i \text{ is Overconfident} \\ 0, & o.w. \end{cases} ;$$

$$Gender_i = \begin{cases} 1, & Male \\ 0, & o.w. \end{cases} ; \quad Minor25_i = \begin{cases} 1, & i \text{ is less than } 25 \text{ years old} \\ 0, & o.w. \end{cases} ;$$

$$European_i = \begin{cases} 1, & i\ is\ European \\ 0, & o.w. \end{cases} \quad ;$$

$$Socials_i = \begin{cases} 1, & Social\ Science\ Background \\ 0, & o.w. \end{cases} \quad ;$$

$$Postgraduate_i = \begin{cases} 1, & Education\ Level\ Higher\ than\ Bachelors \\ 0, & o.w. \end{cases}$$

$$i = 1,2,3 \ldots .77$$

A priory and in line with what has been found in the literature, one expects that gender is a significant variable for explaining overconfidence. In fact, one expects that males exhibit higher levels of overconfidence. One could also expect that overconfident investors risk their wealth much more compared with underconfident, which indicates an inverse relationship between wealth and overconfidence. Also, being younger than 25 years old is a trigger of overconfidence which could be related to the education level. In terms of background, one expects that social science may exhibit overconfidence. To find out, the following table present the results of the logistic regression.

Table 7:
Logistic Regression

```
Random-effects logistic regression              Number of obs      =      1001
Group variable: period                          Number of groups   =        13

Random effects u_i ~ Gaussian                   Obs per group: min =        77
                                                               avg =      77.0
                                                               max =        77

                                                Wald chi2(7)       =    171.82
Log likelihood  = -444.61269                    Prob > chi2        =    0.0000
```

overconfidence	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
wealth	.9984029	.0009446	-1.69	0.091	.9965533	1.000256
gender	10.08488	1.892045	12.32	0.000	6.981923	14.56687
age	.9278153	.022072	-3.15	0.002	.885548	.9721
menor25	.3583454	.0990972	-3.71	0.000	.2084057	.6161607
europeo	.9017443	.1574806	-0.59	0.554	.640368	1.269806
socials	7.70788	1.824171	8.63	0.000	4.847155	12.25697
postgrado	3.119503	.8685267	4.09	0.000	1.807571	5.383633
_cons	1.36e+07	1.29e+08	1.73	0.084	.107722	1.71e+15
/lnsig2u	-15.92989	51.27821			-116.4333	84.57356
sigma_u	.0003474	.0089078			5.21e-26	2.32e+18
rho	3.67e-08	1.88e-06			8.25e-52	1

Likelihood-ratio test of rho=0: chibar2(01) =   0.00 Prob >= chibar2 = 1.000

Marginal effects after xtlogit
y = Linear prediction (predict)
= 1.4708043

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
wealth	-.0015983	.00095	-1.69	0.091	-.003453	.000256	9952.36
gender*	2.311037	.18761	12.32	0.000	1.94332	2.67875	.675325
age	-.0749226	.02379	-3.15	0.002	-.121549	-.028297	24.961
menor25*	-1.026258	.27654	-3.71	0.000	-1.56827	-.484247	.545455
europeo*	-.1034242	.17464	-0.59	0.554	-.445712	.238864	.441558
socials*	2.042243	.23666	8.63	0.000	1.57839	2.50609	.792208
postgr~o*	1.137674	.27842	4.09	0.000	.591984	1.68336	.220779

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Results show that all the variables except being European, are significant variables for explaining overconfidence. To interpret the results, we use the marginal effects of the logit regression. For each additional euro in wealth the likelihood of being overconfident decreases by 0.001. This is in line with what has been mentioned above in terms of the extreme gains and losses experienced by overconfident investors, the more they win the stronger the overconfident gets.

In terms on sex, male investors will be 2,3 times more overconfident than women. This is in line with the descriptive results presented before, in which I presented that males were more confident than females.

For each additional year of age, the likelihood of being overconfident decreases in 0.07. This implies that young investors are more overconfident, and the older the participant the less overconfident. Interestingly, if I divide the sample in younger and older than 25 years old, results suggest that if the investor is younger than 25 years old, he/she is one time less overconfident than those above 25.

If the investor has a background of social sciences, he/she is in average 2 times more overconfident that those from other fields. And if the investor has postgraduate studies, this implies that in average he/she will be 1.1 times more overconfident than those with just bachelors.

To perform a more dynamic analysis, a panel data set was built to explain wealth under overconfidence. The database corresponds to a balanced panel of 13 periods and 1001 observations.

$$\begin{aligned} Wealth_t^i = {} & \beta_0 + \beta_1 Gender_t^i + \beta_2 Age_t^i + \beta_3 Minor25_t^i + \beta_4 European_t^i + \beta_5 Socials_t^i \\ & + \beta_6 Postgraduate_t^i + \beta_6 TurnOverRate_t^i + \beta_6 Overconfidence_t^i \\ & + \beta_6 Elasticity\ A_t^i + \beta_6 Elasticity\ B_t^i + \varepsilon_t^i \end{aligned}$$

$$Gender_t^i = \begin{cases} 1, & Male \\ 0, & o.w. \end{cases} \quad ; \quad Minor25_t^i = \begin{cases} 1, & i\ is\ less\ than\ 25\ years\ old \\ 0, & o.w. \end{cases} \quad ;$$

$$European_t^i = \begin{cases} 1, & i\ is\ European \\ 0, & o.w. \end{cases} \quad ; Socials_t^i = \begin{cases} 1, & Social\ Science\ Background \\ 0, & o.w. \end{cases} \quad ;$$

$$Postgraduate_t^i = \begin{cases} 1, & Education\ Level\ Higher\ than\ Bachelors \\ 0, & o.w. \end{cases} \quad ;$$

$$Overconfidence_t^i = \begin{cases} 1, & i\ is\ Overconfident \\ 0, & o.w. \end{cases} \quad ;$$

$$i = 1,2,3 \ldots .77; \ t = 1,2,3 \ldots .13$$

One of the main drawbacks with the data panel is that if all variables of influence are not available then $Cov\ (X_t^i, \varepsilon_t^i) \neq 0$, ie the residues are not independent of the observations so, ordinary least squared OLS will be biased. To solve this problem, alternative models such a pooled regression nests the data using either fixed or random effects (*See Annex 4*).

Table 8:
Panel data results

```
Random-effects GLS regression                   Number of obs      =      1001
Group variable: period                          Number of groups   =        13

R-sq:  within  = 0.2132                         Obs per group: min =        77
       between = 0.2778                                        avg =      77.0
       overall = 0.1637                                        max =        77

                                                Wald chi2(10)      =    263.79
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
      wealth |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      gender |   21.72342   6.188687     3.51   0.000     9.593813    33.85302
         age |  -4.952064   .6981331    -7.09   0.000     -6.32038   -3.583748
     menor25 |  -87.40884   8.004767   -10.92   0.000    -103.0979   -71.71979
     europeo |  -19.26075   5.424489    -3.55   0.000    -29.89255   -8.628948
     socials |   38.17883   7.238618     5.27   0.000      23.9914    52.36626
   postgrado |  -.1498688   8.046624    -0.02   0.985    -15.92096    15.62123
        trab |  -24.49466   23.95853    -1.02   0.307    -71.45252    22.46319
overconfidence | -16.05203   6.751933   -2.38   0.017    -29.28558   -2.818483
 elasticitya |   12.11236   3.055633     3.96   0.000     6.123428    18.10129
 elasticityb |   .0310212    .003749     8.27   0.000     .0236734     .038369
       _cons |   10103.62   23.95269   421.82   0.000     10056.68    10150.57
-------------+----------------------------------------------------------------
     sigma_u |  42.066602
     sigma_e |   81.55956
         rho |   .2101272   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Results suggest that in average, male investors make 21 euros more than females. For each additional year of age, the wealth of the investor decreases in average 21 euros, however and interestingly, investors younger than 25 years old in average lose 87 euros more compared with those older. If the investor is European, he/she will lose 19 euros in average compared with those from another continent. While if the investor has a background in social science, he/she will win in average 38 euros more than those with another background. If the investor has postgraduate studies, he/she will lose in average 0.14 euros compared with those with just bachelors.

Overconfident investors will lose in average 16 euros more than those underconfident. The elasticity of both shares A and B, are significant variables. An increase of a percental point in the elasticity of A, increases in average the wealth in 12 euros, while an increase of a percental point in the elasticity of B, increases in average the wealth in 0.03 euros.

This last paragraph is quite strong evidence of what this thesis aims to contribute. Overconfident investors perceived less benefits in terms of wealth. One would expect that a ration investor exhibits elastic demands, this implies that in the face of small changes in price, the demand should also change negatively correlated. As my hypothesis states, it seems that overconfident investors exhibit more inelastic demands, which causes the excessive trading and so the strong losses when the shares lose value. As the results of the regression report, when the elasticity increases i.e one would expect a decrease in the demand and so in the revenues perceived by the lack of investments, however, our sample received in average 12 euros extra for share A, and 0.03 euros for share B. This may imply that they perceive increases in the prices as good indicator for buying shares.

4.3 Simulation Results

After the experiment and the econometric analysis was performed, a system dynamics model was developed and calibrated attempting to understand the dynamic mechanisms behind the behaviour of overconfident investors. Particularly to model the feedback loops and effects affecting the demand of overconfident participants.

This model is very simple however it captures the behaviour of the demand for one share. As the main driver for deciding to buy such share is the elasticity affecting the constraint of total amount of possible shares. As mentioned in the literature, and corroborated by the econometrics analysis, this system dynamics model captures the behaviour expected.

Overconfident investors tend to exhibit higher demands, and the question is what drives the excessive trading. The econometric analysis states that there are variables triggering overconfidence, however to keep it in the borders of system dynamics, here I only modelled the two continues variables that seem to explain overconfidence behaviour.

There are some prices in the market that are perceived by the investor. He/she then, based on the wealth, has a maximum available number of shares to buy, however the decision rule for investing is affecting by the elasticity of the investor. Given an elasticity, the investor creates a desired number of shares which is a fraction of the maximum available number of shares, and given the time it takes to buy in the market and comparing the desired with the current number of shares, the decision to buy is done. As under the settings of the experiment, this model assumes that every share bought today is automatically sold the next day. This changes the prices and the quantities, which feedback to the elasticity.

Results of the simulation show that overconfident investors' demand is higher compared with those underconfident (*Left Side Figure 12*). In order to validate to a certain extent, the results of the simulation with those from the micro world, I averaged the number of shares demanded by overconfident and underconfident investors (*Right Side Figure 12*).

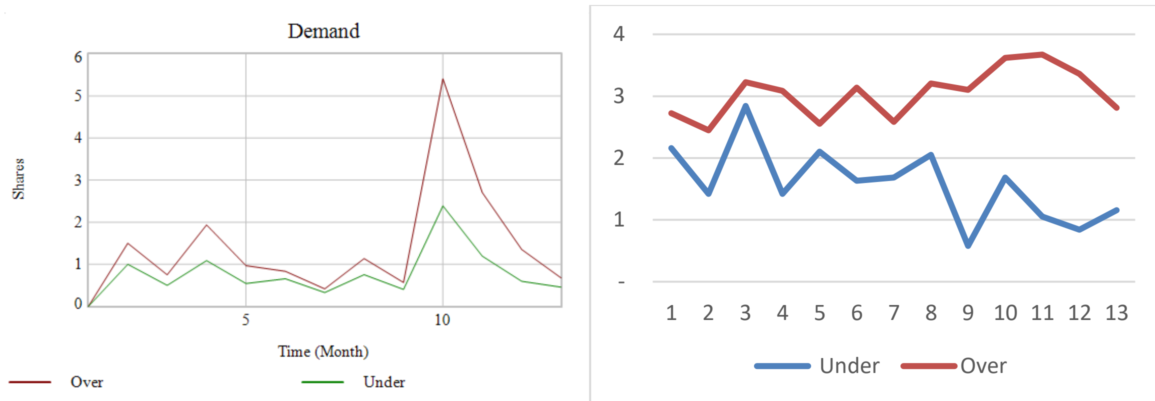


Figure 12: Demand

Overconfident investors tend to demand more shares compared with those underconfident. And although both graphs exhibit different values for each period, the important trend is valid and allows to infer that the structure of the model is capturing the dynamics hypothesis around elasticity affecting the number of shares demanded.

Regarding the changes in wealth, overconfident investors tend to exhibit stronger results either more positive or more negative compared with the behaviour of underconfident investors. Figure 13 corroborates this, in the left side I present the results of the simulation while in the right side I averaged the profits of overconfident and underconfident investors

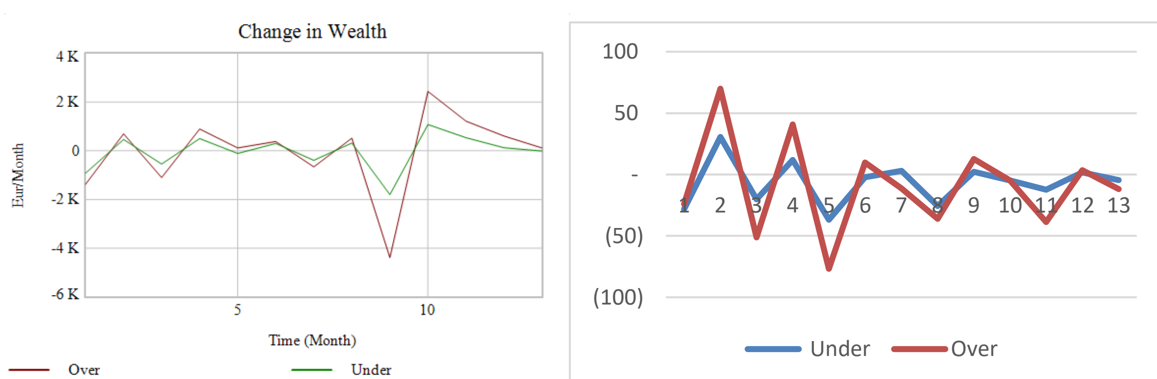


Figure 13: Profits

Overconfident investors tend to risk their wealth in a higher portion compared with underconfident investors. The results of the simulation are presented in the following figure.

Figure 14: Wealth

By these definition, no model can ever be verified or validated, because all models are wrong. In fact, all models, mental or formal, are limited, simplified representations of the real world. They differ from reality in ways large and small, infinite in number (Sterman J. , 2000). System dynamics modelers have developed a wide variety of specific tests to uncover flaws and improve models.

The first validation is called boundary adequacy, this assess the appropriateness of the model boundary for the purpose at hand. The boundary of this model as presented in the causal loop diagram was to capture the process occurring when the participants were investing in the micro world. I consider that the most important concepts for addressing the problem are endogenous to the model. This refers to the prices, demand composition, and changes in wealth. I believe that there is room for studying other important loops that could explain the behaviour of overconfident investors, however for the scope of this thesis, the assumptions behind the structured modelled are enough. Another common type of validation is to prove unit consistency. This assures that the relationship among variables is well constructed (*See Annex 5*).

Summarizing, the micro world generated primary data for performing a regression analysis. Result of this first analysis suggest that wealth, sex, age, background, and academic level are explanatory variables for the presence of overconfidence.

Regarding wealth, overconfident investors lose in average more than those underconfident. The elasticity of both shares A and B, are significant variables and this is quite strong evidence of what this thesis aims to contribute. Overconfident investors perceived less benefits in terms of wealth. It seems that overconfident investors exhibit more inelastic demands, which causes the excessive trading and so the strong losses when the shares lose value.

The simulation model captures the underlying structure that allows to test the dynamic hypothesis around the elasticity exhibited by overconfident investors. And overconfident investors exhibit stronger either wins or losses in wealth, and their trading volume is higher. This implies that overconfident investors are less sensitive to changes in prices and their demands and not directly affected.

5. CONCLUSIONS

Seminal research on portfolio theory based on the efficient market hypothesis seems to rely in strong assumptions such the rationality of investors. Evidence suggests that investment decisions are not always made based on full rationality, and this may be because people may make predictable, non-optimal choices when faced with difficult and uncertain decisions exhibiting heuristics and biases. To understand this, behavioural finance emerged as an alternative approach to incorporate in the study of financial decisions the investor's behaviour.

There is wide research about specific biases affecting the behaviour of investors. In this research, I only studied overconfidence bias, and the relevant concern is how to identify the presence of overconfidence. Previous studies have mostly been undertaken by using questionnaires for extrapolating results as a measure of overconfidence, however the challenge is still to find a plausible measure that is valid.

In the context of financial decision, research suggests that overconfident investors have been characterized by their excessive trading. For measuring this bias, confidence intervals highlight in the literature as a popular measure. However, the limitation for using intervals of confidence is that regardless the significance level we ask the participants, the hit rate will converge always to the same because participants do not adjust the width of their interval.

Another relevant measurement is the average turnover rate, however, 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.

Interestingly, studies about overconfidence are mostly undertaken from a static perspective, however given the nature in which a stock market operates, it would be desirable to research overconfidence from a dynamic perspective in order to dig in the mechanisms triggering the excessive trading of overconfident investors. This research addressed two research questions: i) are stock market investors overconfident, and ii) if so, what are the dynamic mechanisms behind it.

In this research, I investigated the use of the actual average number of transactions proposed by Ho (2011) as a proxy for measuring overconfidence. To do so, I developed a micro world representing a stock market in which participants made decisions for a series of periods and I managed to obtain data for calculating the proxy variable of overconfidence and then conduct econometric analysis of the results.

The overall results of this research allowed to identify that in fact some investors in the stock market are overconfident in their decisions. Much of the research discussed in the literature review seem to report patterns regarding the behaviour of financial market investors affected by overconfidence in terms of their excessive trading.

Results of econometric analysis suggest that wealth, sex, age, background, and academic level are explanatory variables for the presence of overconfidence. Also, very important, overconfident investors lose in average more than those underconfident. And the elasticities are significant variables and this is quite strong evidence of what this thesis contributed.

To identify the dynamic mechanisms behind overconfident behaviour, I developed a system dynamics model that captures two important loops. There is a reinforcing loop for the wealth which as increases, also increases the available capacity to invest, however this loop is counteracted by the elasticity effects which according to the findings of the micro world, overconfident investors tend to exhibit lower elasticities which explains the excessive investment and major number of shares acquired in every period in comparison with underconfident investors. In sum, with this model I managed to model that overconfident investors exhibit more inelastic demands, which causes the excessive trading and so the strong losses when the shares lose value.

It is important to highlight that the findings of this research are in line with what has been found in previous research. I contributed to generate more evidence about overconfidence in the stock market investors, and the underlying dynamics effects affecting the behaviour of the investors in terms of wealth and elasticities.

As limitation of this study, I believe that the settings under which the experiment works is still simple. Also, the number of participants in the micro world was only 77. And the system dynamics model only considers two main loops affecting the behaviour of overconfident investors.

For future research, I suggest to improve the settings of the experiment. This new version will be a simultaneous game in which prices will be composed given the movements in the experiment market. Also, I 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. There is also room for improving the system dynamics model. If one manages to find more variables explaining overconfidence, one could model them in a system dynamics approach to generate insights about the dynamics mechanisms behind it.

ANNEXES

Annex 1. Instructions for the experiment

The following are the literal instructions the participants receive at the beginning of the experiment.

Welcome to the experiment. The following are important instructions about the settings of the experiment, please read them carefully and any enquiry just communicate it to the instructor.

- This micro world represents a simplification of a stock market in which you can buy shares from two companies named A and B.
- In each of the periods, you have updated information about the price and return of each of the shares and your task is to decide how many shares to buy from each share, in case you want to buy.
- You are not forced to invest in every period
- You cannot invest more than what you have in money.
- Your goal is to maximize your wealth which starts at 10.000 euros.
- The total number of shares you buy in the current period will be sold at market price in the next period.
- The experiment lasts for 13 periods.

Annex 2. Logbook for the experiment

The following are the guidelines for conducting the experiment at the decision lab.

Activity	Notes	Time
Log into the main computer	User: E1499673 Password: M-Visa24	5 Minutes 8.30 to 8.35
Connect to the server	.\dl-docent Computer: 131.174.236.12 Password: doc1943#	5 Minutes 8.35 to 8.40
Turn on the rest of computers	Use DL-Wake and check they are all turned on.	5 Minutes 8.40 to 8.45
Connect all computers to the server	Select all the computers and click on Logon User: E828196 Password: Onderwijs123#	10 Minutes 8.45 to 8.55
Start Zleaf in all computers	Select all computers and click on Launch and Select 367 all.	5 Minutes 8.55 to 9.00
Start the experiment		
Instructions	Tell all the rules and objective. Remind to obtain their consent for participating	10 Minutes 9.00 to 9.10
Practice rounds	Practice together	5 Minutes 9.10 to 9.15
Round 1	Participants make decisions	2 Minutes 9.17 to 9.19
Round 2	Participants make decisions	2 Minutes 9.19 to 9.21
Round 3	Participants make decisions	2 Minutes 9.21 to 9.23
Round 4	Participants make decisions	2 Minutes 9.23 to 9.25
Round 5	Participants make decisions	2 Minutes 9.25 to 9.27
Round 6	Participants make decisions	2 Minutes 9.27 to 9.29
Round 7	Participants make decisions	2 Minutes 9.29 to 9.31
Round 8	Participants make decisions	2 Minutes 9.31 to 9.33
Round 9	Participants make decisions	2 Minutes 9.33 to 9.35
Round 10	Participants make decisions	2 Minutes 9.35 to 9.37
Round 11	Participants make decisions	2 Minutes 9.37 to 9.39
Round 12	Participants make decisions	2 Minutes 9.39 to 9.41
Round 13	Participants make decisions	2 Minutes 9.41 to 9.43
End of the Experiment		
Collect results	Import the results	15 Minutes 9.45 to 10.00

Annex 3. Arima Model

ARMA models are the result of combining Auto Regressive (AR) and Moving Average (MA) schemes for times series analysis. The theory states that stationary time series can be modelled as a combination of past values and/or past errors. The approach proposed by Box and Jenkins came to be known as the Box-Jenkins methodology to Auto Regressive Integrated Moving Average models (ARIMA) (Box & Jenkins, 1970) (Box & Pierce, 1970).

Arima Model for Share A

Dependent Variable: D(LOG(A),1)
Method: Least Squares
Date: 05/15/17 Time: 19:07
Sample (adjusted): 2014M04 2017M07
Included observations: 40 after adjustments
Convergence achieved after 15 iterations
MA Backcast: 2014M03

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-1.071067	0.079313	-13.50425	0.0000
AR(3)	0.393452	0.090789	4.333690	0.0001
AR(6)	0.295348	0.080722	3.658816	0.0008
AR(8)	-0.223357	0.073964	-3.019795	0.0047
MA(1)	0.999853	0.078560	12.72733	0.0000

R-squared	0.461223	Mean dependent var	0.003300
Adjusted R-squared	0.399649	S.D. dependent var	0.036797
S.E. of regression	0.028511	Akaike info criterion	-4.160556
Sum squared resid	0.028452	Schwarz criterion	-3.949446
Log likelihood	88.21113	Hannan-Quinn criter.	-4.084226
Durbin-Watson stat	2.038541		

Inverted AR Roots	.69+.20i	.69-.20i	.27-.73i	.27+.73i
	-.62+.70i	-.62-.70i	-.88+.22i	-.88-.22i
Inverted MA Roots	-1.00			

The ARIMA model for share A is:

$$Ret_t = -1.071067 * Ret_{t-1} + 0.393452 * Ret_{t-3} + 0.295348 * Ret_{t-6} - 0.223357 * Ret_{t-8} + 0.999853 e_{t-1}$$

Annex 4. Panel Data

When dealing with a panel data, we must check if the sample has individual effects that explain the behaviour of the variables, then we must apply the panel data methodology. If, on the other hand, this type of condition is not observed, i.e. no individual effects exist, then an analysis using OLS would be consistent and the most efficient.

Breusch-Pagan Lagrange Multiplier test:

- This is a test for the random effects model based on the OLS residual.
- Test whether σ_u^2 or equivalently $Cor(\, u_{it}, u_{is})$ is significantly different from zero.
- If the LM test is significant, use the random effects model instead of the OLS model.
- We still need to test for fixed versus random effects.

When applying the Breusch-Pagan test, results show a $\chi^2 = 3.95$, showing $Prob > \chi^2 = 0.0470$, then there enough evidence to reject the null hypothesis which says that the variance is constant, then we accept that there are heteroskedasticity problems. Such problems can be fixed by performing a data panel with either fixed or random effects.

To decide which effect is the most appropriate (fixed or variable) estimator, I used the Hausman test. 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.

Hausman test

- The random effects estimator is more efficient so we need to use it if the Hausman test supports it. If it does not support it, use the fixed effects model.
- Hausman test tests whether there is a significant difference between the fixed and random effects estimators.
- The Hausman test statistic can be calculated only for the time-varying regressors.
- The Hausman test statistics is:

$$H = (\hat{\beta}_{RE} - \hat{\beta}_{FE})'(V(\hat{\beta}_{FE}) - V(\hat{\beta}_{FE}))(\hat{\beta}_{RE} - \hat{\beta}_{FE})$$

- It is chi-square distributed with degrees of freedom equal to the number of parameters for the time-varying regressors.
- If the Hausman test is insignificant use the random effects.
- If the Hausman test is significant use the fixed effects.

The Hausman test yielded a $\chi^2 = -0.83$. Sometimes, when there are few individuals in the sample result, the test, i.e. the value of the χ^2, can throw a negative number (which is impossible) but that for the purposes of the test should be interpreted as strong evidence that the null hypothesis cannot be rejected. I reject the null hypothesis, that is, there is no correlation between the individual effects and the explanatory variables, indicating that the random estimator must be chosen.

Arima Model for Share B

Dependent Variable: D(LOG(B),1)
Method: Least Squares
Date: 05/15/17 Time: 19:20
Sample (adjusted): 2015M02 2017M07
Included observations: 30 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(15)	-0.192315	0.062912	-3.056873	0.0049
AR(18)	-0.121111	0.063154	-1.917713	0.0654

R-squared	0.239801	Mean dependent var	0.019142
Adjusted R-squared	0.212651	S.D. dependent var	0.058742
S.E. of regression	0.052123	Akaike info criterion	-3.006083
Sum squared resid	0.076070	Schwarz criterion	-2.912670
Log likelihood	47.09124	Hannan-Quinn criter.	-2.976199
Durbin-Watson stat	2.379366		

Inverted AR Roots	.91-.18i	.91+.18i	.76+.49i	.76-.49i
	.49-.67i	.49+.67i	.34+.76i	.34-.76i
	.05-.91i	.05+.91i	-.30+.88i	-.30-.88i
	-.61-.70i	-.61+.70i	-.81+.41i	-.81-.41i
	-.83-.09i	-.83+.09i		

The ARIMA model for share B is:

$$Ret_t = -0.192315 * Ret_{t-15} - 0.121111 * Ret_{t-18}$$

With these equations, the returns as well as the prices were forecasted. And these new prices are the market prices the participants face for the upcoming periods. For every round of the experiment, the participant receives updated information about the market until completing the 13 periods.

Annex 5. Model Documentation

Table 9:
Model variables

Variable	Equation	Units
Desired Shares	$Number\ of\ Possible\ Shares^{Demand\ Elasticity}$	Shares
Buying Rate	$\frac{Desired\ Number\ of\ Shares\ -\ Demand}{Time\ to\ Buy}$	Shares/Month
Selling Rate	$\frac{Demand}{Time\ to\ Sell}$	Shares/Month
Change in Wealth	$Selling\ Price * Selling\ Rate\ -\ Buying\ Price * Buying\ Rate$	Euro/Month
Number of Possible Shares	$\frac{Wealth}{\text{Buying Price}}$	Shares
Demand Elasticity	$\frac{Change\ in\ Demand}{\text{Change in Price}}$	Dimensionless
Wealth	$\int_{1}^{13} Change\ in\ Wealth, 10000$	Euro
Demand	$\int_{1}^{13} Buying\ Rate - Selling\ Rate, 0$	Shares
Buying Price	$Lookup\ [(1{,}900) - (100{,}1000)], (1{,}918), (2{,}932), (3{,}929), (4{,}929), (5{,}933), (\ldots (7{,}916), (8{,}920), (9{,}907), (10{,}913), (11{,}908), (12{,}902), (13{,}900)$	Eur/Shares/Month
Selling Price	$Lookup\ [(1{,}890) - (100{,}950)], (1{,}933), (2{,}929), (3{,}933), (4{,}922), (5{,}916), (\ldots (7{,}907), (8{,}913), (9{,}908), (10{,}902), (11{,}900), (12{,}897), (13{,}897)$	Eur/Shares/Month

REFERENCES

Alpert, M., & Raiffa, P. (1982). A progress report on the training of probability assessors. En D. Kahneman, P. Slovic, & A. Tversky, *Judgment UnderUncertainty: Heuristics and Biases* (págs. 294–305.). Cambridge, England: Cambridge Univ. Press.

Alti, A., & Telock, P. (2014). Biased Beliefs, Asset Prices, and Investment: A Structural Approach. *The Journal of Finance*, 325-361.

Baker, K., Nofsinger, & John. (2002). Psychological Biases of Investors. *Financial Services Review*, 97-116.

Barber, B. M., & Odean, T. (1999). The Courage of Misguided Convictions. *Financial Analysts Journal*, 41-55.

Barber, B., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance*, 773–806.

Barber, B., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *Quarterly Journal of Economics*, 261-292.

Bar-Yosef, S., & Venezia, I. (2014). An Experimental Study of Overconfidence in Accounting Numbers Predictions. *International Journal of Economic Sciences*, 78-89.

Biais, B., Hilton, D., Mazurier, K., & Pouget, S. (2005). Judgemental Overconfidence, Self-Monitoring, and Trading Performance in an Experimental Financial Market. *Review of Economic Studies* , 287-312.

Blavatskyy, P. (2009). Betting on own knowledge: Experimental test of overconfidence. *Journal of Risk and Uncertainty*, 39–49.

Box, G., & Jenkins, G. (1970). *Time Series Analysis, Forecasting and Control.* San Francisco: Holden-Day.

Box, G., & Pierce, D. (1970). Distribution of the Residual Autocorrelations in Autoregressive-Integrated Moving-Average Time Series Models. *Journal of the American Statistical Association*, 1509-1526.

Brehmer, B. (1992). Dynamic decision making: human control of complex systems. *Acta Psychologica*, 211-241.

Brehmer, B., & Dörner, D. (1993). Experiments with computer-simulated microworlds: Escaping both the narrow straits of the laboratory and the deep blue sea of the field study. *Computers in Human Behavior*, 171–184.

Burton G, M. (2003). *The Efficient Market Hypothesis and Its Critics.* Princeton, New Jersey: Princeton University. CEPS Working Paper No. 91.

Buskens, V. (2015). Rational Choice Theory in Sociology. *International Encyclopedia of the Social & Behavioral Sciences (Second Edition)*, 901–906.

Chandra, A. (2008). Decision Making in the Stock Market: Incorporating Psychology With Finance. *National Conference: FFMI 2008 IIT* (págs. 1-28). Kharagpur: Munich Personal RePEc Archive.

Chapman, L. (1967). Illusory Correlation in Observational Report. *Journal of Verbal Learning and Verbal Behaviour* , 151-155 .

Chen, G., Kim, K., Nofsinger, J., & Rui, O. (2007). *Trading Performance, Disposition Effect, Overconfidence, Representativeness Bias, and Experience of Emerging Market Investors*. Obtenido de Social science research network: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=957504

Chuang, W.-I., & Lee, B.-S. (2006). An empirical evaluation of the overconfidence hypothesis. *Journal of Banking & Finance* , 2489–2515.

Cosenz, F. (2015). Conceptualizing Innovative Business Planning Frameworks to Improving New Venture Strategy Communication and Performance. A Preliminary Analysis of the “Dynamic Business Model Canvas”. . *XXXVII AIDEA Conference, Piaceza*.

Davis, J. P., Eisenhardt, K. M., & Bingham, C. B. (2007). Developing theory through simulation methods. *Academy of Management*, 480-499.

De Gooyert, V. (2016). Nothing so practical as a good theory; Five ways to use system dynamics for theoretical contributions. *Proceedings of the 34th International Conference of the System Dynamics Society* (págs. 1-10). Delft, the Netherlands: System Dynamics Society.

Elbanna, S. (2006). Strategic decision-making. Process perspectives. *International J. of Management Reviews. 8*, 1-20.

Fama, E. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Finance*, 383-417.

Fischbacher, U. (2007). Z-Tree: Zurich Toolbox for Ready-made Economic Experiments. *Experimental Economics 10(2)*, 171-178.

Forrester, J. (1961). *Industrial Dynamics.* Cambridge, MA: MIT Press.

Frank, J. D. (1935). Some Psychological Determinants of the Level of Aspiration. *American Journal of Psychology*, 285-293.

Funke, J. (1995). Experimental research on complex problem solving. En P. Frensch, & J. Funke, *Complex problem solving: The European perspective* (págs. 243–268). Hillsdale, NJ: Lawrence Erlbaum Associates.

Gasser, S. M., Rammerstorfer, M., & Weinmayer, K. (2017). Markowitz revisited: Social portfolio engineering. *European Journal of Operational Research*, 1181–1190.

Getmansky, M., & Papastaikoudi, J. (2002). *Extrapolating Expectations: An Explanation for Excess Volatility and Overreaction.* Cambridge MA: Sloan School of Management.

Gigerenzer, G., Hoffrage, U., & Kleinbölting, H. (1991). Probabilistic mental models: A Brunswikian theory of confidence. *Psychological Review*, 506–528.

Gilovich, T., Griffin, D., & Kahneman, D. (2002). *Heuristics and Biases: The Psychology of Intuitive Judgment.* Cambridge: Cambridge University Press.

Glaser, M., & Weber, M. (2003). Momentum and turnover: Evidence from the German Stock Market. *Schmalenbach Business Review*, 108–135.

Glaser, M., & Weber, M. (2007). Overconfidence and trading volume. *The Geneva Risk and Insurance Review*, 1–36.

Glaser, M., Langer, T., & Weber, M. (2013). True Overconfidence in Interval Estimates: Evidence Based on a New Measure of Miscalibration. *Journal of Behavioral Decision Making*, 405–417.

Gonzalez, C., Vanyukov, P., & Martin, M. K. (2005). The use of microworlds to study dynamic decision making. *Computers in Human Behavior*, 273–286.

Goodwin, P., & Wrigh, G. (2014). Heuristics and biases in probability assessment. Chapter 10. En P. Goodwin, & G. Wrigh, *Decision Analysis for Management Judgment.* New Delhi, India: John Wiley & Sons Ltd.

Grinblatt, M., & Keloharju, M. (2009). Sensation Seeking, Overconfidence, and Trading Activity. *The Journal of Finance*, 549-578.

Groesser, S. (2012). *Stichwort: System dynamics.* Heidelberg: Gabler Wirtschaftslexikon.

Grossman, S., & Stiglitz, J. (1980). On the Impos sibility of Informationally Efficient Markets. *The American Economic Review*, 393-408.

Harrison, J. R., Carrol, G. R., & Carley, K. (2007). Simulation modelling in organizational and management research. *Academy of Management Review*, 1229-1245.

Heffernan, S. A. (1990). A characteristics definition of financial markets. *Journal of Banking & Finance Volume 14, Issues 2–3*, 583–609.

Ho, C. M. (2011). Does Overconfidence Harm Individual Investors? An Empirical Analysis of the Taiwanese Market. *Asia-Pacific Journal of Financial Studies*, 658–682.

Juslin, P., Winman, A., & Olsson, H. (2000). Naïve empiricism and dogmatism in confidence research: A critical examination of the hard – easy effect. *Psychological Review*, 384–396.

Kehneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision Under Risk. *Econometrica 47, 2*, 263-291.

Klayman, J., Soll, J., Gonzales-Vallejo, C., & Barlas, S. (1999). Overconfidence: It Depends on How, What and Whom You Ask. *Organizational Behavior and Human Decision Processes*, 216–247.

Kunda, Z. (1987). Motivated Inference: Self-Serving Generation and Evaluation of Causal Theories. *Journal of Personality and Social Psychology*, 636-647.

Langnickela, F., & Zeisbergerb, S. (2016). Do we measure overconfidence? A closer look at the interval production task . *Journal of Economic Behavior & Organization*, 121-133.

Lichtenstein, S., & Fischhoff, B. (1977). Do those who know more also know more about how much they know? . *Organizational Behavior and Human Performance*, 159–183.

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance, 7 (1)*, 77–91.

Meucci, A. (2009). Managing Diversification. *Bloomberg Education & Quantitative Research and Education Paper*, 74-79.

Morecroft, J. (1988). System dynamics and microworlds for policy makers. *European Journal of Operational Research*, 301-320.

Morecroft, J. D., & Sterman, J. D. (1994). *Modeling for learning organizations.* Portland: OR, Productivity Press: System Dynamics Series.

Nawrocki, D. N., & Viole, F. (2014). Behavioral Finance in Financial Market Theory, Utility Theory, Portfolio Theory and the Necessary Statistics: A Review. *Journal of Experimental and Behavioral Finance*, 10-17.

Odean, T. (1998). Are investors reluctant to realize their losses? *Journal of Finance*, 1775–1798.

Parikh, P. (2011). *Value Investing and Behavioral Finance.* New Delhi : Tata Mcgraw Hill.

Pikulina, E., Renneboog, L., & Tobler, P. N. (2017). Overconfidence and investment: An experimental approach. *Journal of Corporate Finance*, 175–192.

Pompian, M. M. (2006). *Behavioral Finance and Wealth Management.* USA: John Wiley & Sons.

Provenzano, D. (2002). An artificial stock market in a system dynamics approach. *20th System dynamics conference.* Palermo: System dynamics society.

Russo, J., & Schoemaker, P. (1992). Managing overconfidence. *Sloan Management Review*, 7–17.

Senge, P. (1990). *The Fifth Discipline: The Art and Practice of the Learning Organization.* New York: Doubleday.

Sewell, M. (2010). *Behavioural Finance.* Cambridge: University of Cambridge.

Shleifer, A. (2000). *Ineficient Markets: A Introduction to Behavioral Finance.* Oxford: Oxford University Press.

Statman, M., Thorley, S., & Vorkink, K. (2006). Investor overconfidence and trading volume. *The Review of Financial Studies 19*, 1531–1565.

Sterman, J. (2000). *Business Dynamics. Systems thinking and modeling for a complex world.* Boston: Mc Graw Hill.

Sterman, J. D., Henderson, R., Beinhocker, D, E., & Newman, L. I. (2007). Getting big too fast: Strategic dynamics with increasing returns and bounded rationality. *Management Science*, *53(4)*, 683–696.

Subash, R. (2012). *Role of Behavioral Finance in Portfolio Investment Decisions: Evidence from India.* Prague: Charles University in Prague. Faculty of Social Sciences. Institute of Economic Studies.

System Dynamics Society. (08 de 05 de 2017). *System Dynamics Society*. Obtenido de http://www.systemdynamics.org/what-is-s/

Szegö, G. P. (1980). Investment Decisions Under Uncertainty. En G. P. Szegö, *Portfolio Theory. With Application to Bank Asset Management* (págs. 1–20). Bergamo, Italy: Academic Press.

Taylor, S., & Brown, J. D. (1988). Illusion and Well-Being: A Social Psychological Perspective on Mental Health. *Psychological Bulletin*, 193-210.

Teigen, K., & Jørgensen, M. (2005). When 90% confidence intervals are 50% certain: on the credibility of credible intervals. *Applied Cognitive Psychology*, 455–475.

Toma, F.-M. (2015). Behavioral Biases of the Investment Decisions of Romanian Investorson the Bucharest Stock Exchange. *Procedia Economics and Finance*, 200-207.

Turkle, S. (1984). *The second self: Computers and the human spirit.* London: Granada.

Tversky, & Kahneman. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185*, 1124-1131.

Tversky, & Kahneman. (1983). Extensional Versus Intuitive Reasoning: The Conjunction Fallacy in Probability Judgment. *Psychological Review*, 293-315.

Weinstein, N. D. (1980). Unrealistic Optimism About Future Life Events. *Journal of Personality and Social Psychology*, 806-820.

Yahoo Finance. (17 de 05 de 2017). *Yahoo Finance*. Obtenido de https://finance.yahoo.com/