# ESTUDOS II

FACULDADE de ECONOMIA da UNIVERSIDADE do ALGARVE

# ESTUDOS II

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**Economia e Desenvolvimento Regional**

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# Are security analysts rational? - A literature review [1]

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## Abstract

Rational choice theory and bounded rationality constitute the basis for the discussion in several areas regarding human rationality. In finance, this discussion has been made between traditional finance and behavioural finance approach, which have different perspectives concerning market agents' rationality. This paper reviews several studies addressing rationality among security analysts. The analysis shows that analysts' systematic optimism seems to be inconsistent with rationality. The discussion of analysts' optimism is made using two main theories for their biased behaviour: cognitive and economic-based explanations. We review literature on over-optimism, under and overreaction, economic incentives, herding behaviour and analysts' preference to withhold unfavourable forecasts. The paper concludes with suggestions for further research.

**Keywords**: Rationality, biased behaviour, security analysts, cognitive bias, economic incentives

## Resumo

A teoria da escolha racional e a racionalidade limitada constituem a base de diversas discussões em diferentes áreas em torno da racionalidade humana. Em finanças, esta discussão tem sido realizada entre as finanças tradicionais e as finanças comportamentais, as quais apresentam perspectivas diferenciadas relativamente à racionalidade dos agentes de mercado. Este estudo examina diversos trabalhos relacionados com a racionalidade dos analistas financeiros. A análise sugere que o sistemático optimismo dos analistas aventa inconsistência com a perspectiva racional. A discussão em torno do optimismo dos analistas é efectuada com base em duas teorias que

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justificam o seu comportamento enviesado: justificações de ordem cognitiva e económica. A revisão de literatura foca o sobre-optimismo, sub e sobre reacção, incentivos económicos, "*comportamento de manada*" e preferência dos analistas em ocultar previsões desfavoráveis. O estudo termina com sugestões para investigação futura.

**Palavras-Chave**: Racionalidade, comportamento enviesado, analistas financeiros, enviesamento cognitivo, incentivos económicos.

## 1. Introduction

The issue of rationality has also been discussed in several areas of knowledge without consensus. In the course of this discussion, the different perspectives about the degree of human rationality are drawn from two different views about human behaviour. Rational choice theory proponents argue that human judgment can be modelled mathematically, suggesting that people optimize their decision processes in order to find the "*one best solution*". The alternative perspective, bounded rationality, states that the previous theory is not realistic since people's limited analytical capacities prevent anything near complete rationality.

In finance, there are two competing approaches to understanding financial markets. The traditional finance framework posits that agents satisfy the conditions of completeness and transitivity, and therefore, behave as fully rational Bayesians maximizers of a subjective utility function. Behavioural finance constitutes the alternative approach, which is consistent with the arguments of the bounded rationality perspective. Behavioural finance states that some financial phenomena can be better understood using models that consider some agents as not being fully rational.

Considering the nature of their work, financial analysts are viewed as a sophisticated group of decision-makers acting in financial markets. Consequently, these market agents present a unique opportunity to analyse and test the two competing theories in finance and to provide further evidence in the debate between full and bounded rationality. Easterwood and Nutt (1999) present one of the clearest definitions of rationality in the security analyst context. They state that "*a rational analysis of analyst behavior predicts that analysts immediately and without bias incorporate information into their forecasts*". Under this definition, evidence collected through empirical research suggests that analysts are, in fact, not rational in the sense that their forecasts are biased (e.g., de Bondt and Thaler, 1990; Trueman, 1994; Easterwood and Nutt, 1999; Ahmed et al., 2000; Beckers et al., 2004). One of the most important ideas extracted from this body of literature is that analyst forecasts are optimistic. This optimism is derived from the systematic positive difference between forecast and actual earnings per share (EPS) (e.g., Stickel, 1990; Abarbanell, 1991; Brown, 1997; Easterwood and Nutt, 1999) and the permanent higher number of buy recommendations compared with the number of sell recommendations (e.g., Womack, 1996; Ho and Harris, 1998; Ryan and Taffler, 2004).

Two principal explanations for this non-rational behaviour are cognitive-bias explanations and economic incentives-based explanations (Kothari, 2001). Broadly speaking, cognitive-bias explanations argue that financial agents use heuristics and rules of thumb[1] when they process information. Under this assumption, analysts are subject to the same biases as subjects in laboratory experiments. In fact, evidence of analysts' "*systematic asymmetric*" reaction conditional on the nature of information (Amir and Ganzach, 1998; Easterwood and Nutt, 1999) is better understood under the cognitive-bias approach. On the other hand, economic incentive-based explanations advocate that agency problems underlie analysts' optimism. In fact, the literature suggests that analysts' working environment and incentives can lead to several distortions in their analyses.

The discussion behind rationality in market agents is crucial since this issue constitutes the basis of several debates in accounting and finance. Despite the strong theoretical background behind the traditional finance framework, should we ignore empirical evidence showing that, in general, agents present biased behaviour? This question raises a critical issue in the development of finance theory: should we continue to develop research based on the premise that agents are fully rational or should we relax this strong assumption? Analyst behaviour constitutes a unique opportunity to clarify these issues, since they act as sophisticated agents and markets recognize the importance of their opinions (e.g., Stickel, 1991; Womack, 1996; Ho and Harris, 1998; Park and Stice, 2000; Barber et al., 2001; Barber et al., 2003; Ryan and Taffler, 2004).

This paper is structured as follows. Section two discusses the concept of rationality and describes two different approaches to human behaviour drawn from this concept. In addition, it reviews two competing theories in finance that have different views about rationality: traditional finance and behavioural finance. Section three justifies the importance of security analysts' opinions to the market and summarises the main explanations for analyst-biased behaviour. This section also reviews several papers that present evidence supporting each of these explanations for analysts' biased behaviour. Section four concludes, presenting suggestions for further research.

## 2. The concept of rationality

Classical economic theory is based on the concept of rationality (Arrow, 1986). Classical economists, like Smith and Ricardo, sustained the development of this discipline in notions that are closely related with this concept. Several examples of rational behaviour are present in the discourse of these classical economists: the preference for more rather than less, the investment in industries yielding the highest rate of return, the minimization of costs or profit maximization, among others (Arrow, 1986). Nowadays, economists' definition of rationality is based on the concepts of transitivity (if x>y and y>z, then x>z) and completeness (choices can be ranked), which together represent the

[1] Literature defines rules-of-thumb as "algorithms", "heuristics", or "mental models".

maximization of a function.[2] This approach emerged only in the 1950s since before that time, economists assumed that people were motivated by "*self-interest*" (Arrow, 1986).

Traditional finance draws on classical economics to develop models that explain financial markets based on the assumption that market participants are rational (Barberis and Thaler, 2003). According to Barberis and Thaler (2003), rationality has two meanings: 1) when agents receive new information they update their beliefs correctly, particularly in the manner described by Bayes' law and 2) given their beliefs, agents make choices that are normatively acceptable, in the sense that they are consistent with Savage's (1972) notion of Subjective Expected Utility (SEU).

The present section briefly illustrates the foundations of rational behaviour, namely the two main theories behind this issue: rational choice theory and bounded rationality. It also examines the implications of rationality in finance. In particular, we present two different approaches that have different assumptions about this topic: traditional finance and behavioural finance.

### 2.1. Rational choice theory

Rational choice theory differs from other perspectives that see human action as involving both rational and non-rational elements. This perspective denies the existence of any other type of action than the purely rational and calculative one (Scott, 2000), suggesting full rationality in decision-makers.[3] Turner (1991) presents five assumptions of rational choice theory:

1. Humans are purposive and goal oriented;
2. Humans have sets of hierarchically ordered preferences, or utilities;
3. In choosing lines of behaviour, humans make rational calculations;
4. Emergent social phenomena - social structures, collective decisions, and collective behaviour - are ultimately the result of rational choices made by utility-maximizing individuals;
5. Emergent social phenomena that arise from rational choices constitute a set of parameters for subsequent rational choices of individuals.

These five points reveal that the rational process is very demanding, assuming that people are goal oriented and, conditional on their preferences, they can find the "*one best*

[2] The function may be related to utility, costs, profits, among other variables.

[3] The apparent success of economics in explaining human behaviour as a function of money and by the possibility of making a profit, leads other social sciences in this direction (Scott, 2000). According to Scott (2000), these social scientists have tried to build theories around the idea that all action is fundamentally rational in nature and that people do the cost / benefit analysis before making a decision.

*solution*". It is particularly noteworthy that rational choice theory suggests that individuals are able to state their preferences by their wants or goals, and that these preferences motivate the actions taken by individuals. This framework also posits that individuals must anticipate the outcome of every alternative course of action, calculate which will be the best for them and choose the alternative that is likely to give them the greatest satisfaction (Coleman, 1973; Heath, 1976). This means that fully rational man knows the solution of all complex mathematical problems, regardless their level of difficulty (Selten, 2001). For the defenders of this framework, the available mathematical tools, in particular the rules of Bayes and Bernoulli, are seen as descriptions of actual human judgement (Datson, 1981). The understanding of these complex assumptions leads us to conclude that people are required to have unlimited cognitive capabilities whenever taking fully rational decisions.

Hatch (1997) presents a model with five steps that defines a typical rational decision-making process in organizations, which can be generalized to decision-makers. The first step of the model is to define the problem and the collection of relevant information. The following step is the generation and evaluation of all the possible alternatives available, considering the likelihood of the positive and negative consequences of each one. After that, decision-makers should choose the best possible alternative, given their set of objectives. The last steps consist of the implementation of the selected alternative and monitoring the results. In a dynamic perspective, this last action will lead to the first step of the model and to another optimized decision.

The specific limitations of organizations and human capacities provide the arguments that some scholars have used to criticize the assumptions of rational models. Simon presents some limitations of rational decision-making models, which are inconsistent with full rationality (Hatch, 1997):

1. Imperfect and incomplete information;
2. The complexity of problems;
3. Human information-processing capacity;
4. The time available for decision-making processes;
5. The conflicting preferences decision-makers have for organizational goals.

These limitations represent the starting point for the development of an alternative to rational choice models: bounded rationality.

## 2.2. Bounded rationality

Bounded rationality theory emerged as a critique to rational choice theory. The empirical evidence and the observation of human behaviour suggest a fundamental role for limited cognition as an aspect of decision-making, something that is not captured by

the neo-classical framework. Under this alternative perspective, humans attempt to be rational but their limited capacities prevent anything near complete rationality (Perrow, 1993). The existence of such limitations restricts the usefulness of rational choice assumptions in understanding the actual behaviour of decision-makers; people are simply unable to follow such demanding processes. Herbert Simon introduced the idea of bounded rationality, originally a psychological concept, into economics.[4] Since then, bounded rationality has started to be viewed as the main alternative to neo-classic rationality.

One of the main critiques to rational choice is that people cannot consider all their options in choosing their solutions to given problems. Put simply, decision-makers do not have complete knowledge of the alternative courses of action available to them or they cannot afford to attain that knowledge. Moreover, even if people knew all their alternatives, it would be almost impossible to rank them according with their preferences (Simon, 1997). As a result, people tend to simplify available alternatives and select the first acceptable one.

Several studies document many other restrictions to optimal choice. Klein (2001) presents eleven boundary conditions for optimizing decisions that review the main assumptions presented in the literature:

1. The goals must be well defined, in quantitative terms (Koopman and Pool, 1991);
2. The decision-maker's values must be stable (Fischhoff, 1991; Slovic, 1995; March, 1978);
3. The situation must be stable (Pitz, 1992);
4. The task is restricted to selection between options (Berkeley and Humphreys, 1982);
5. The number of alternatives generated must be exhaustive (Janis and Mann, 1977; Koopman and Pool, 1991);
6. The optimal choice can be selected without disproportional time and effort (Gigerenzer and Todd, 1999; Minsky, 1986; von Winterfeldt and Edwards, 1986);
7. The options must be thoroughly compared to each other (Janis and Mann, 1977);
8. The decision-maker must use a compensatory strategy (Janis and Mann, 1977);
9. The probability estimates must be coherent and accurate (Beyth-Marom et al., 1991);

[4] Conlisk (1996) presents in his survey four reasons that justify the incorporation of bounded rationality in economic models: 1. There is abundant empirical evidence showing the importance of bounded rationality; 2. Models of bounded rationality have proved themselves in a wide range of impressive work; 3. The standard justifications for assuming unbounded rationality are unconvincing and 4. Deliberation about an economic decision is a costly activity, and good economics requires that we entertain all costs.

10. The scenarios used to predict failures must be exhaustive and realistic (Pitz, 1992);
11. The evaluation of each scenario must be exhaustive (Pitz, 1992).

It is noteworthy that the existence of these restrictions to optimal choice does not mean that bounded rationality is the same as irrationality. Indeed, we cannot substitute rationality by irrationality just because people's behaviour fails to conform the norms of full rationality. A decision maker who is guided by an aspiration adaptation mechanism rather than utility maximization may be perfectly rational (Selten, 2001), even if he or she does not choose the "*one best decision*".[5] Considering that decision-makers do not have the unlimited cognitive capacities that are required to achieve optimal solutions, Herbert Simon developed an alternative theoretical framework. Under this alternative perspective, the satisfying agent takes the place of the rational agent and satisficing behaviour substitutes the model of global rationality. This satisficing agent is not making a mistake when he chooses his non-optimal payoff, because satisficing involves choosing an alternative that exceeds some criterion or target (Simon, 1997). In fact, satisfice means selecting the first course of action that appears to be successful, even if it is not the best (Klein, 2001).

### 2.3. Rationality implications in finance

Considering that rationality is a central issue in the development of finance, the rational choice theory and the bounded rationality alternative have implications in the finance domain. The next sections describe two alternative approaches in the finance world that are based on the previous discussion.

#### 2.3.1. Traditional finance

Rational optimization of agents and equilibrium constitute the two pillars of traditional finance literature. The rational choice perspective supports the economic definition of rationality, which is embedded in two important concepts: completeness and transitivity. This approach is largely based on an unrealistic picture of human decision-making, which assumes that economic agents are fully rational Bayesian maximizers of subjective utility.[6] One of the reasons that explain why Bayes' theorem was used to build

[5] Simon (1956) develops two alternatives to utility maximization in order to explain decision-making processes: adjusting the aspiration level and adjusting the set of behavioural alternatives. He described decision-making as a search process guided by aspiration levels. An aspiration level is a value of a goal variable that must be reached or surpassed by a satisfactory decision alternative. However, aspiration levels are not permanently fixed but are rather dynamically adjusted to the situation. Aspiration levels are raised if it is easy to find satisfactory alternatives and lowered if satisfactory alternatives are hard to obtain (Selten, 2001). Search for alternatives, satisficing and aspiration adaptation constitute three main concepts in Simon's view of bounded rationality.

[6] Bayes's theorem is a mathematical formula used for calculating conditional probabilities that figures prominently in subjectivist or Bayesian approaches. Subjectivists, who maintain that rational belief is governed by the laws of probability, lean heavily on conditional probabilities in their theories of evidence and their models of empirical

economic theory and financial modelling is their nonarbitrary characteristic, which is a useful discipline to modelling, although the evidence on heuristics and biases suggests that Bayesian updating is not fully descriptive of human behaviour (Hirshleifer, 2001).[7] Bayesians assume that agents have a coherent preference structure that is characterized axiomatically and defines a notion of a probabilistic mixture of outcomes. These rational agents care about utilitarian characteristics, do not commit cognitive errors, have perfect self-control, are always risk averse and are never averse to regret (Statman, 1999). The traditional finance framework is highly analytical and normative, assuming a world dominated by *homo economicus*, who is fully rational and focused on utility maximization.

Despite the strong theoretical background behind traditional finance perspective, several studies document price behaviour and decision-making processes inconsistent with rational expectations models.[8] According to Sandroni (2005), there are two causes for the documented anomalies: agents suffer from cognitive biases when forming beliefs (do not process information according to Bayes' rule) or do not have sufficient information to hold correct beliefs.

### 2.3.2. Behavioural finance

Behavioural finance relaxes the assumption that agents form beliefs according to the laws of probability and assumes that simpler heuristic rules are used (Sandroni, 2005). This new approach seeks to incorporate the implications of psychological decision processes in the decision-making process (Olsen, 1998). Behavioural finance draws on an extensive experimental literature on judgment under uncertainty that suggests that people do not behave consistently with the rules of probability and statistics (Griffin and Tversky, 2002). Given that time and cognitive resources are limited, natural selection has designed minds that implement rules-of-thumb selectively to a subset of cues (Hirshleifer, 2001). Olsen (1998) presents two reasons for the current interest in behavioural finance: the empirical evidence that alternative financial theories seem to be deficient in fundamental ways, and the development of prospect theory.

There are several papers documenting empirical inconsistencies with the traditional finance paradigm.[9] These inconsistencies constituted the starting point for the development of the behavioural finance theory, which is seen as an emerging alternative to traditional finance. Behavioural finance is constituted by two building blocks: psychology and the limits to arbitrage[10] (Shleifer and Summers, 1990).

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learning. Bayes's theorem is used to calculate the formally optimal rule about how opinions, meaning probabilities, should be revised based on new information (Edwards, 1982). According to this approach, these probabilities are just numbers between zero and one that represents the extent to which a somewhat idealized person believes a statement to be true.

[7] Indeed, several studies suggest that agents do not update their beliefs correctly since people seem to be influenced by "irrelevant alternatives" (Hirshleifer, 2001).

[8] See Daniel et al. (1998) and Barberis and Thaler (2003) for a literature review of financial anomalies.

[9] For a first approach see the article compilations in Thaler (1993) and Thaler (2005).

[10] For an introduction, see Barberis and Thaler (2003).

Given the experimental work showing that people systematically violate SEU theory when choosing among risky gambles (Barberis and Thaler, 2003), several non-SEU theories have been developed in the last few decades.[11] One of the best-known non-SEU theories is prospect theory. Kanheman and Tversky (1979) introduced prospect theory as a critique of expected utility theory. According to SEU theory, utility derives solely from the probability distribution of payoffs resulting from a choice, ignoring people's regret aversion (Hirshleifer, 2001). Kanheman and Tversky (1979) contend that choices made among risky prospects are inconsistent with the basic tenets of the SEU theory. This alternative approach is based on more realistic behaviour assumptions to explain how people deal with loss in making choices in the face of risk and uncertainty, namely capturing the documented risk aversion.[12]

## 3. Analyst behaviour

Financial analysts play a central role in financial markets. There are several reasons justifying academic research related to analysts' work and their behaviour in financial markets.[13] Additionally, there is empirical evidence showing that market prices move in the direction of analysts' recommendations and earnings estimates (e.g., Stickel, 1991; Womack, 1996; Ho and Harris, 1998; Park and Stice, 2000; Barber et al., 2001; Barber et al., 2003; Ryan and Taffler, 2004). Considering that financial analysts are sophisticated agents, can we expect rationality in analysts' behaviour? This section discusses several biases that are inconsistent with rational behaviour and concludes with an overview of several empirical papers that document the biased behaviour of financial analysts.

### 3.1. The importance of analysts' opinion to the market

De Bondt and Thaler (1990) set out three reasons justifying the interest in this particular group of market agents. Firstly, research suggests that earnings forecasts and forecasts revisions influence stock prices. Secondly, research advocates that analysts are

[11] Barberis and Thaler (2003) present a list of the better known models based on non-SEU theories.

[12] According to the proponents of prospect theory, individuals maximize a weighted sum of "values" (analogous to utilities) where the weights are not based on true probabilities, but in functions of probabilities (Hirshleifer, 2001). Another difference is that extremely low probabilities are treated as impossibilities, and extremely high probabilities as certainties. However, very (but not extremely) low probabilities are overestimated, and very (but not extremely) high probabilities are overestimated. For the intermediate probabilities, the weighting function increases with a slope less than one.

[13] There are two different categories of analysts: "sell-side analysts" and "buy-side analysts". Sell-side analysts are security analysts employed by banks and brokerage firms, who release information to markets. "Buy-side analysts" are employed by institutional investment firms. Although both analyst categories make recommendations, sell-side analysts are the primary producers of earnings forecasts (Schipper, 1999).

rather good at what they do since their forecasts often outperform time-series models (e.g., Conroy and Harris, 1987). Thirdly, the precision of analyst expectations represents a natural upper boundary to the quality of the earnings forecasts of less sophisticated agents, since most investors cannot produce their own predictions.

Thousands of analysts follow a large population of companies and produce regular reports evaluating firms' securities. Usually, each analyst follows ten to twenty stocks in a given industry or economic sector, which makes them industry specialists (Schipper, 1991). Analysts are considered sophisticated agents given their importance as intermediaries between firms and investors. These sophisticated agents collect, process and disseminate information to current and prospective investors. Their privileged access to information may lead us to believe that the stocks they recommend will experience superior performance.[14]

A vast amount of literature suggests that analysts' information releases influence stock prices. In fact, analysts' outputs, such as earnings estimates and changes in recommendations influence the evaluation of security prices (e.g., Stickel, 1991; Stickel, 1992; Womack, 1996; Ho and Harris, 1998; Park and Stice, 2000; Barber et al., 2001; Barber et al., 2003; Ryan and Taffler, 2004). Empirical research finds that, on average, the markets react favourably to positive changes in recommendations and have a negative reaction to a drop in recommendations. In one of the most frequently cited papers in this area, Womack (1996) finds strong evidence that stock prices are significantly influenced by analysts' recommendation changes. Using US data, he finds significant initial price and volume reaction in the three-day event period around the recommendation change. However, in the case of new buy recommendations, most price impact occurs around the announcement date, while the new sell recommendations have a longer impact.[15]

### 3.2. Is analysts' judgement rational?

Ackert and Hunter (1995) define the main characteristics for rational expectations in two separate categories. First, the forecast errors, conditional on the available information set, should have zero means (orthogonality property of rational expectations). Second, the forecast errors should be uncorrelated with the values of all the variables in the information set, and therefore, with their own past values (lack of serial correlation property).

Considering the Easterwood and Nutt's (1999) definition of rational analyst behaviour, evidence suggests that analysts' systematic optimism is inconsistent with rationality. However, the analysts' apparently biased behaviour may not imply a non-

[14] Beckers et al. (2004) mention that individual and institutional investors use analysts' reports when they make portfolio selections or revision decisions. Additionally, they also state that analysts' earnings forecasts are used in equity valuation models.

[15] The post-recommendation drift associated with buy recommendations is significant and short lived (+2.4 percent for the first post-event month), but the post-recommendation drift associated with sell recommendations is larger and longer (-9.1 percent for the first six-month post-event period).

rational behaviour. In fact, Ackert and Hunter (1994) show that analysts' forecasts are converging towards rational expectations from a dynamic perspective. Moreover, Acker and Hunter (1995) argue that some of the papers claiming analysts' non-rational behaviour present methodological inadequacies, like ignoring the necessary orthogonality property and the use of samples with aggregation problems. More recently, Lim (2001) has presented an alternative explanation for analysts' optimistic behaviour. He suggests that optimistic forecasts may be consistent with rationality if they act to decrease forecast errors. In fact, by issuing optimistic forecasts, analysts are improving their access to firms' management and thus, contributing to a possible increase in their accuracy.

### 3.3. Analysts' optimism

Despite the clear relevance of analysts' opinions to the market, much of the financial literature claims that analyst judgement is biased. In fact, several studies identify patterns in analysts' behaviour inconsistent with analysts' rationality (e.g., de Bondt and Tahler, 1990; Trueman, 1994; Easterwood and Nutt, 1999; Beckers et al., 2004). One of the most important ideas extracted from the literature is that the biased behaviour is usually connected (implicitly or explicitly) with analysts' optimism. In fact, almost all of the analyst studies identify patterns systematically consistent with optimism.

The tendency to be optimistic is verified in different markets and different periods of time. Research on analysts' forecasts in the UK, US and Europe, considering samples from 1976 to date, points to a significant excess of optimism. The main reason justifying this optimistic analyst behaviour is related to the systematically positive difference between forecasted and actual earnings per share (e.g., Brown, 1997; Easterwood and Nutt, 1999).[16] In fact, the literature suggests that analysts tend to be optimistic in their analyses, and that optimism is most pronounced in some specific situations. The studies addressing analysts' optimism reveal that tendency towards optimism is particularly manifested in situations of financial distress. In fact, optimism seems to be more evident for failing firms (Moses, 1990), loss-making firms (Das, 1998), firms with past poor performance (Lim, 2001) and during periods of negative earnings growth (Ding et al., 2004). Even considering samples of bankrupt firms, analysts maintain this tendency (Moses, 1990 and Espahbodi et al., 2001).

The literature also suggests that the magnitude of errors in analysts' forecasts depends on the number of analysts following the firms. Studies like Brown (1997), Lim (2001) and Beckers et al., (2004) find that analysts' optimism seems to be more evident

[16] The systematically higher number of buy recommendations compared with the number of sell recommendations, particularly in the US, is another reason consistent with analysts' optimism. In fact, one major difference between US and UK studies is the ratio of new buy to new sell recommendations. Considering US studies, the ratio is approximately 7:1 (Womack, 1996) and between 4.1:1 and 5.2:1, depending on rating system used (Ho and Harris, 1998). Using UK data, Ryan and Taffler (2004) calculate a ratio of 2.3:1, which suggests that UK analysts appear to be less optimistic than their US counterparts.

when firms have a smaller number of analysts following them. On the other hand, the studies' results propose that firm's size can explain the degree of optimism in analysts' forecasts. Although Beckers et al. (2004) do not corroborate this idea for an European sample, Brown (1997) and Lim (2001) find higher levels of optimism for small firms and firms not listed in the S&P 500. This relation seems to be consistent with the excessive optimism for firms whose earnings were hard to predict in the past (Huberts and Fuller, 1995), firms with lower absolute values of earnings forecasts (Brown, 1997) and firms with higher volatility (Lim, 2001). Additionally, the company's sector seems to influence the level of analysts' optimism given their significant effect on analysts' accuracy (Brown, 1997; Beckers et al, 2004). Finally, other consistent findings among the papers analysed is the decline of optimism as the forecast horizon gets closer to the earnings announcement (Amir and Ganzach, 1998; Das, 1998).

There are several reasons for analysts' non-rational behaviour. Kothari (2001) identifies two main explanations: behavioural cognitive-bias explanations and economic incentives-based explanations. In the following sections, the paper discusses these reasons and present empirical evidence attesting these and other explanations.

### 3.3.1. Analysts'cognitive-bias explanation

Cognitive biases that describe analysts' judgement are drawn from the psychological literature that presents evidence of non-rational behaviour in several circumstances. Although some of these psychological effects have potential relevance to security markets, economists have traditionally been sceptical in accepting the relation between psychological effects and markets. The main argument to criticise this approach is that errors are independent across individuals and that they cancel out in equilibrium (Hirshleifer, 2001). However, the experimental psychology literature presents a vast number of studies documenting systematic biases in human behaviour.[17] In a comprehensive survey about investor psychology and asset pricing, Hirshleifer (2001) argues that heuristic simplification, self-deception, and emotional loss of control provide a unified explanation for most known judgment and decision biases.

#### 3.3.1.1. Over-optimism

The tendency to be over-optimistic is one of the best documented psychological errors. Montier (2002) states that such over-optimism results from a number of psychological biases, such as illusion of control and self-attribution. The first bias means that people feel themselves to be far more in control of a situation than they often actually are. The illusion of control, which has a positive correlation with the increase of information, manifests itself when people believe that they have influence over the outcome of uncontrollable events. This illusion of control, which influences the belief that

[17] See Gilovich et al., 2002 for a comprehensive review.

a person can favourably influence unrelated chance events, is defined by Hirshleifer (2001) as a type of "*magical thinking*" given the belief in relations between causally unrelated actions or events.

The self-attribution bias means that people attribute favourable outcomes to skill while bad outcomes are attributed to bad luck, or else they blame external factors for failure (e.g. Fischhoff, 1982; Langer and Roth, 1975; Miller and Ross, 1975 or Taylor and Brown, 1988). The empirical psychology literature reports that as individuals observe the outcomes of their actions, they update their confidence in their own ability in a biased manner, leading to overconfidence (Daniel et al., 1998). This bias contrasts with the economists' view that people learn from past mistakes.

#### 3.3.1.2. Overreaction and underreaction

Behavioural finance relies on a vast body of literature documenting patterns of returns that cannot be understood in the context of classical pricing theory to criticize the efficient market hypothesis. One of the main critiques to this alternative framework is that some aspects of the anomalous returns patterns documented in the behavioural literature seem contradictory. In fact, behavioural opponents ask for an integrated theory to explain these phenomena in addition to explanations offered for particular anomalies.[18] One of the most cited cases of contradictions is the apparent market underreaction and overreaction in different contexts (Daniel et al., 1998).

Daniel et al. (1998) present one of the theories developed to fill this gap based on investor overconfidence about the precision of private information and variations in confidence arising from biased self-attribution. According to their theory, the difference between stock price overreaction and underreaction is the type of the information: stock prices overreact to private information and underreact to public signals. Their theory is based on experimental studies which find that individuals underestimate their error variance in making predictions, and overweight their own forecasts relative to those of others. This differentiation between over and underreaction has implications not only for investors, but also for security analysts since both generate information for trading such as interviewing management, verifying rumors, and analysing financial statements. In overestimating his ability to generate information, an investor or analyst will underestimate his forecast errors leading to overconfidence about his private information, but not to public signals received by all (Daniel et al., 1998). The theory presented by Daniel et al. (1998) to explain the over or underreaction assumes that, when the investor

[18] Fama (1998) criticizes this result from the behavioural finance approach. In his view, the overreaction and underreaction phenomena cancel each other out and thus the market should, on average, converge to its fundamental value. He also argues that behavioural finance is unable to provide a proper framework to explain when over and underreaction should be expected.

receives confirming public information, his confidence rises, but disconfirming information causes confidence to fall only moderately.

Other important theory explaining the over and underreaction phenomenon states that the nature of the reaction is conditional on the nature of the information. De Bondt and Thaler (1990) and O'Hanlon and Whiddett (1991) present conflicting results regarding the under and overreaction in analysts' forecasts. In fact, using US data, de Bondt and Thaler (1990) claim for overreaction while O'Hanlon and Whiddett (1991), using UK data, claim for underreaction. This contradictory results were justified by O'Hanlon and Whiddett (1991) with the possible effects of different remuneration systems and different investment regulation between the US and UK. However, Capstaff et al. (1995) and de Bondt and Forbes (1999) find overreaction in UK analysts, which contradicts O'Hanlon and Whiddett's (1991) explanation. Abarbanell and Bernard's (1992) results are in line with O'Hanlon and Whiddett (1991), given that they find evidence consistent with analysts' forecast underreaction. Although Abarbanell and Bernard (1992) support the argument of analysts' forecasts being to extreme, they reject the overreaction phenomenon since their results fail to relate extremely high forecasts with firms recently experiencing strong earnings performance, or extremely low forecasts with firms experiencing weak earnings forecasts. This condition to overreaction motivated Amir and Ganzach (1998) and Easterwood and Nutt (1999) to divide analysts' forecasts conditional to the nature of the information preceding the forecast: good news and bad news. Broadly speaking, these two studies find that analysts underreact in the presence of good news and overreact in the presence of bad news, consistent with systematic optimism. This explanation seems to clarify the conflicting results in previous literature and is consistent with behavioural theories justifying asymmetric behaviours. Finally, Espahbodi et al. (2001) present evidence supporting this different reaction given the analysts' underreaction to the bankruptcy.

### 3.3.2. Economic incentives-based explanations

The economic incentives represent a major explanation for analysts' optimism. According to Easterwood and Nutt (1999), the economic incentives can broadly be divided into two characteristics: the direct incentive to promote the purchase of stocks, and the indirect incentive of access to the top executives.

Cote and Goodstein (1999) argue that observers of the security industry writing in the popular press, practitioner journals and academic journals have raised concerns related to the pressure that some security analysts face to release positive recommendations. This pressure is related to analysts who work for firms that also have an investment banking function. In fact, analysts' compensation for their corporate finance arm in investment banking firms is one of the main explanations in the literature for analysts' optimistic behaviour. Analysts' working environments and their incentives can lead to several distortions. According to Michaely and Womack (2005), investment banks traditionally have three income sources that may potentially create conflicts of interests within the bank and with its clients: 1) corporate financing, the issue of securities and merger

advisory services; 2) brokerage services and 3) proprietary trading. Some of the main potential conflicts are between the two first sources. The first is responsible primarily for completing transactions for new and current clients, and the second for maximizing commissions and spreads by providing timely, high quality and presumably unbiased information to their clients.

Many security analysts who work for full-service brokerage firms are partly compensated based on the brokerage commissions they generate (Konrad and Greising, 1989). Therefore, this compensation works as an incentive to release favourable recommendations instead of unfavourable ones. As Espahbodi et al. (2001) argue, by issuing an optimistic forecast for a company, the firm's brokers can call investors to buy that company's stock and thus receive brokerage commissions. By issuing pessimistic forecasts, the commissions generated are lower for the firm due to restrictions on short sales and the limited availability and greater risk for options. In this context, Carleton et al. (1998) argue that brokerage firms tend to be significantly more optimistic in predicting future investment performance than non-brokerage houses. In fact, brokerage houses and investment banks employ most of the analysts.

Analysts' need to maintain good relations with the management of the firms they follow is pointed to as another incentive to optimism. Lim (2001) and Das et al. (1998) argue that analysts' optimism can be explained by their need to gain increased access to information from management. In fact, analysts depend on corporate management for accurate and timely information about the companies they follow. Companies use this dependency as a weapon against analysts who issue negative opinions on their stock (Espahbodi et al., 2001). On the other hand, optimism seems to be more pronounced for companies that have more uncertain information environments and for analysts who are more dependent on management access as a source of company information (Lim, 2001). By issuing negative recommendations, analysts are not only potentially reducing their access to the firm but also reducing the possibility of their investment banking firm doing business with that firm in the future.

There are several papers suggesting that the agency interpretation can justify, at least partially, analysts' optimistic forecasts and recommendations. For instance, Dugar and Nathan (1995) show that investment banker analysts produce more optimistic forecasts than non-investment banker analysts. Hodgkinson's (2001) results are in line with Dugar and Nathan (1995) since she finds that the close relation between firms and analysts working for broker firms provides more optimistic forecasts than analysts who do not have that relation. The argument used to justify this situation is similar to Lim (2001), who suggests that analysts' need to improve their access to firms' management to benefit from this key source of non-public company information. Michaely and Womack (1999) present further evidence on Dugar and Nathan's (1995) argument of agency conflicts regarding broker analysts with investment banking relations. In fact, they find that underwriter analysts' recommendations of IPO firms have significantly worse performance than non-underwriter analysts. Additionally, Hong and Kubik (2003) mention analysts' career concerns as relevant to explain analysts' optimism, since brokerage houses seem to reward analysts for their optimism.

### 3.3.4. Cognitive or economic incentives-based explanations?

Although there are papers stating that cognitive biases constitute the explanation for analysts' optimism, and others arguing that economic factors are behind this behaviour, there is no consensus regarding what constitutes the real explanation for this phenomenon. The lack of consensus is related to the difficulties that researchers face to isolate each explanation; however, Tamura (2002) presents evidence supporting the cognitive explanation since he advocates that analysts are affected by their personalities in forecasting. In fact, a relatively optimistic analyst tends to continue to be optimistic, while a pessimistic analyst tends to continue pessimistic. Contrary to this, Stevens and Williams (2004) suggest that human decision bias is unlikely to be the cause for analysts' optimism given the results of their experimental research. These contrary results indicate that perhaps there is no "*one explanation*". Therefore, research on this issue is needed to understand the weight that each explanation has in the justification of analysts' optimism.

### 3.3.5. Other explanations

#### 3.3.5.1. Herding behaviour

The finance literature advocates that analysts tend to compare themselves with one another, exhibiting herding behaviour. Generally, herding behaviour can be defined as individuals using a consensus opinion to modify their private beliefs (Cote and Sanders, 1997). In the earnings estimation context, herding refers to the tendency of forecasters to "*shade*" or move their published earnings forecasts toward those of their colleagues (Olsen, 1996). Beckers et al. (2004) present a review of the academic research findings related to herding behaviour among financial analysts:

1. The tendency to herd the consensus increases with the number of estimates close to the consensus and with the inaccuracy of one's own past estimates (Stickel, 1990; Graham, 1999);
2. Older analysts are more likely to produce forecasts that deviate from the consensus, and conversely, younger analysts are typically less bold than their older counterparts (Hong et al., 2000);
3. The tendency to herd has no relationship to the accuracy of the consensus forecast (Welch, 2000);
4. Herding increases with earnings unpredictability (Olsen, 1996).

Shiller (1995) suggests that herding can be observed in several contexts, but it is more exposed when the decision-making is complex and limited by time, information and

ability. In fact, one of most frequently mentioned scenarios for herding behaviour is the purchase recommendations for individual stocks by security analysts (Welch, 2000). Cote and Sanders (1997) argue that forecasters display those characteristics when producing corporate earnings forecasts. If these forecasts are affected by herding, estimates can become biased and can lead to suboptimal investment decisions. In particular, herding can also create inaccuracy in published earnings estimates (Olsen, 1996).

Trueman (1994) and Olsen (1996) argue that the tendency to comparison can lead to risk aversion, and that such risk averse behaviour causes herding. One possible explanation for this situation is that analysts' compensation may be determined by comparison with other analysts' forecasts, rather than accuracy. Olsen (1996) justifies this possibility by the difficulty in measuring the quality of earnings estimates given the large random component in earnings. Two different empirical papers find herding behaviour among analysts in the UK and US markets. Using UK data, de Bondt and Forbes (1999) show that although absolute errors increase with the forecast horizon, analysts' disagreement remains almost unchanged. Welch (2000) finds that the most recent two revisions by other analysts have a positive influence on the next analyst revision.

#### 3.3.5.2. Analysts' preference to withhold unfavourable forecasts

McNichols et al. (1997) investigate analysts' optimism from a different perspective. Instead of focusing on the incentives that analysts have to issue optimistic forecasts, these authors examine their disincentives to disclose negative information. Specifically, McNichols et al. (1997) explore whether analysts are more likely to report on stocks about which they have favourable views. The results suggest analysts' preference to withhold unfavourable forecasts, since analysts tend to start covering firms they view favourably and stop covering firms they view unfavourably. In fact, McNichols et al. (1997) show that stocks recently added into analysts' lists of followed stocks are heavily weighted toward "*Strong Buy*" recommendations compared with other stocks with previous recommendations. In contrast, stocks dropped by analysts tend to have lower ratings than those whose coverage continues. McNichols et al. (1997) reinforce the fact that their results should be interpreted as partial explanation for analysts' optimism by refusing the idea that analysts introduce less forecast bias near the end of coverage. The authors support this view, arguing that analysts do not report forecasts when they drop stocks from coverage. Consequently, analysts do not reflect negative information in their final sample of observed forecasts and thus the final sample of observed forecasts will be, on average, too high given the selection conditional to their expectations.

## 4. Conclusions and suggestions for further research

In this paper, we present a brief description of the two main theories that constitute the basis of several discussions in different areas: rational choice theory and bounded rationality. These two perspectives influenced the development of two competing theories describing financial markets: Traditional finance and behavioural finance.

We review several papers claiming for a non-rational behaviour regarding a specific group of market agents. In fact, finance literature suggests that security analysts are biased in their judgement and they do not incorporate information into their forecasts immediately. Considering the documented biases, we conclude that serious doubts exist regarding analysts' rationality. One of the strongest ideas concerning these studies is that analysts are systematically optimistic in their forecasts. Although studies documenting that analysts' are optimistic in general situations, little is known about their specific behaviour in extreme situations. As Schipper (1991) points out, it makes sense to investigate decision strategies in these scenarios, because research suggests that optimism seems to be most pronounced in forecasts preceded by share price declines or earnings declines.

Therefore, it seems to be important to explore thoroughly how analysts deal with bad news. The study of analysts' anticipation and response to bad news events can provide even clearer evidence of analysts' optimism and their role in the apparent delayed impact of bad news on investors. The nature of analysts' anticipation of and response to bad news can be addressed by analysing actual analyst reports for the period around a pre-determined negative event, namely before and after it has become known by the general public. A qualitative analysis based on analysts' reports can be useful in order to understand if their discourse provides additional evidence that it is not possible to assess with the traditional approach of analysing the stock market response to recommendations and earnings forecasts.

There is also a wide range of literature presenting different explanations for this biased behaviour. The two most important explanations are related to cognitive and economic issues. Further research is needed to understand the weight of each explanation regarding security analysts' optimism. The study of scenarios where economic incentives are absent can provide an important contribution to the understanding of this phenomenon. For instance, the study of audit qualified firms can provide a unique opportunity to test the importance of cognitive explanations in analyst behaviour. Given that analysts' economic incentives to promote the purchase of stocks with audit qualifications is diminished as well as their incentives to increase their access to top executives, the study of analyst recommendation and forecasts on these firms can help to clarify if the cognitive biases are present in these sophisticated market agents. The connection between analyst behaviour and audit qualifications can be interesting since these two areas of literature have been developed separately until now. This connection may represent a contribution to both accounting and finance literature and can provide further evidence on the main discussion of this paper.

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