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# How predictive are analyst's forecasts? A behavioural finance's view

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# Part I

# Introduction

The objective of this thesis is to study the accuracy of financial analysts from a behavioural finance perspective. We decided to focus on the target prices these professionals set in order to develop the causes and consequences of the difference with the actual stock prices. These target prices are an integral part of the reports of financial analysts who are employed by investment banks or brokerage firms. By analysing this quantitative component of financial reports, a better understanding of the magnitude of the different types of error is possible. The evaluation of the accuracy of predictions allows us to establish a scheme of the behaviour of financial analysts when composing these reports. As suspected, these analysts, like all human beings, are subject to several psychological biases.

In order to answer our research question, this thesis is divided in two main parts. The first part is devoted to a review of the literature composed of both traditional theories and behavioural finance theories. First, the main classical theories based on the assumption that the markets are efficient, namely the Random Walk and the Capital Asset Pricing Model, are reviewed. Second, theoretical and empirical evidence discrediting the three forms of the efficient market hypothesis are presented. The momentum effect and the refutation of the impossibility of arbitrage are detailed. Third, the history of behavioural finance and the cognitive and emotional biases most represented in the psychological and economic literature are detailed. Fourth, we conclude this section by defining the profession of financial analysts as well as their reports, which are at the heart of our study. Finally, we delve deeper into the behavioural biases to which these professionals are the most subjected.

The second part of this thesis consists in an empirical analysis towards target prices of

two European indexes: the AEX (Dutch) and the BEL20 (Belgian). To do so, we analyse the target prices of the companies included in these indexes during the period 2010-2020. As a first step, we compile various descriptive statistics on the companies selected in the two indexes as well as different measures, continuous or discrete, on the accuracy of the forecasts. Then, we set up simple linear regressions in order to study a possible correlation between the accuracy and different variables such as the market momentum, the role of past accuracy or the quality of firms' environment. Finally, we shed light on our observations from a behavioural finance point of view. For this, we evaluate the presence of the two most common biases among financial analysts: over-optimism and overconfidence.

# Part II

# Literature Review

## 1 Review of traditional theories

### 1.1 Different efficiencies situations

With respect to the economic literature, efficiency can take three different significations depending on the approach adopted.

First, with regard to the allocation of the assets, a market is considered as efficient when the price of the assets moves to equalize the adjusted marginal rates of returns for the different risk among all savers and investors.

Second, the operational perspective stipulates that the efficiency of a market is defined by the level of the transaction costs. The way these fees are fixed should limit brokers and other market participants to aspire only to competitive profits.

Third, from an informational point of view, the efficiency of a market is agreed when all the information available is reflected in the assets' prices. That is, these prices represent the real economic value of the assets (Broquet, 1997).

It is important to emphasize that the efficient market hypothesis only relates to the completion of the informational character of the efficiency. Even if the three notions are interrelated, their confusion would lead to misinterpretations and abusive conclusions on the market efficiency (Colmant, Gillet, & Szafarz, 2003).

## 1.2 Principal Theories

### 1.2.1 Random Walk

In *Random Walk in Stock Market Prices*, (Fama, 1965) tried the **chartist theories** that had gained interest until the 1960s to predict the stock price evolution. These methods approached the stock market evolution by finding patterns in past evolution of the price behaviour and assuming that they would repeat themselves. Thus, "sequence of price changes prior to any given day is important in predicting the price change for that day". However, as this approach could sometimes lack clarity, analysts were more likely to rely on a second method to price a security: the **intrinsic value method**. This procedure stipulates that factors such as the quality of management or the perspective of evolution in the industry at a specific time are of particular importance when determining earning potentials and thus the intrinsic value of the stocks. By analysing the fundamental factors underlying the prices, any expert could discover the over- or undervaluation of a security and therefore predict which trend would follow the stock price to line up on its intrinsic value.
Fama described an efficient market:
"*A market where there are large numbers of rational, profit- maximisers actively competing with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants* (Fama, 1965, p. 56)".

The intra competition among agents leads to a situation where the actual price of a security is a good proxy of its intrinsic value. Indeed, as the prices should incorporate all the actual and anticipated information, the actions of the competitors have a marginal effect by inducing only a random movement of the prices around their intrinsic value.

On average, every variation of an individual factor affecting the intrinsic value of a stock price will be fully reflected in the actual price of the stock. Hence, the instantaneous adjustments

taken by the market will be equally often the result of an over-evaluation than its opposite. Similarly, the complete adjustment that follows successive new intrinsic values is just as often premature than delayed.

In a real and uncertain world, the intrinsic value of securities is never agreed which creates inconsistencies with the actual prices. However, the systematic nature of these gaps allows in the long run the smarter market participants to adjust their prediction and *in fine* neutralize this discrepancy.
Under the random walk theory, past knowledge cannot be used in a meaningful way to predict the future path of stocks' returns.

To prove so, Fama (1965) tested the independency of successive price changes first by statistical means such as serial correlation coefficients or runs of consecutive price changes in the same direction. Then, he evaluated the different mechanical trading rules to see whether the profits they provide are greater than a static trading strategy. The serial correlation tests on the successive price changes gave coefficients extremely close to zero. Technical theorists or chartists could raise concerns on the validity of the statistical techniques used to show the independency of successive price changes. In their opinion, these methods are uncomplete since they fail to capture the complexity embodied in the patterns they track. In response to this, more sophisticated technical methods such as the filter rule went also through prosecution. With this method, a position is held unless a change in the price is higher in absolute value than the threshold fixed. Neither the size nor the presence of the filter affect the previous results found by some pairs (Cootner, 1962; Kendall, 1953) on the higher profitability of a static trading strategy compared to mechanical trading rules. These results supported the validity of the random walk model.

However, even in a random walk context it is thought that the higher ability of some

analysts to identify the presence of divergences between the intrinsic value and the prices or situations where the intrinsic value in itself is affected give them higher returns than following a simple buy-and-hold policy. Some analysts have a higher ability for identifying two types of divergences which imply higher returns than following a simple buy-and-hold policy. These two types of divergences occur when a discrepancy between the intrinsic value (IV) and the price is observed, or in situations where the IV in itself is affected.

The high incidence of those analysts helps to raise the efficiency of the markets implying a closer conformity to the random walk setting. Besides the consistent outperformance of the analysts over a random selection of the stocks comprised in the same range of riskiness, costly tools are also required to produce these challenging pickings. That is to say, only open-end mutual funds analysts have been so far capable to meet these requirements by adding value mobilizing elements of fundamental analysis. However, the diversification gained by the pooling of many resources may be the only reason to this superior performance. Indeed, Wharton (1962) countered claims on the alleged proximity of the managers with the market due to their skills, converging with the above description of the random walk accuracy.

Fama (1970) managed to mathematically prove the results previously delivered in 1965 and formalized the link between the efficient market hypothesis and the random walk model. For this, he established the number of arbitragers needed to pretend to efficiency. Theory implied the trading of assets promising the same cash flow at the same price, or in other words the non-existence of arbitrage opportunities.

### 1.2.2 Empirical foundation

In the 1960's and during more than 30 years, numerous empirical studies verified the authenticity of the efficient market hypothesis (EMH). Now, the definition of this efficient market is a function of the system of information considered as available. Three degrees have been adopted and enabled to evaluate to which extend prices are able to incorporate sensitive information with regards to the value of an asset. These progressive forms are determined on

the one hand from the speed of information's incorporation and on the other hand from the coherence during the process.

In the **weak form** of market efficiency, the current price of an asset is a function of its entire price history. Thus, future changes are meant to be random because the current share price already includes the historical content. Under this hypothesis, returns cannot be higher than a simple buy-and-hold policy. Tests proving the inaccuracy of technical theories are supportive of the weak form of market efficiency hypothesis on which is based the random walk theory.

The **semi-strong form** of market efficiency tackles markets' reactivity to public information such as a release of dividends. As soon as this information is available, it should be totally incorporated in the share price. Obviously, the faster this incorporation is, the more efficient the market will be considered. To rule on the veracity of the second strongest form of efficiency, average accumulated residuals are measured. The method allows an isolation of the impact of a particular information at a certain time.

The **strong form** of market efficiency takes into consideration the reaction of the markets to private information and public information. The prices of the assets traded in an efficient market under this standpoint fully reflect public information as well as the private one detained by privileged agents. Literature stipulates that individuals with this privileged access can be classified in two categories. However, results on "initiated investors" proved the inefficiency of the market. This subcategory of investors are aware of pertinent figures that are not publicly released thanks to their position or the scope of their participation in an organisation. Provided that initiated investors are capable of releasing excess returns, both types of information are not reflected in the current prices.

The two first floors of market efficiency do not seem to be repudiated in the literature and are even supported by empirical evidence. Now, the possibility of its declination under its latest form, the strong form, found a clear denial in the economic literature. Nonetheless, the

presence of some anomalies prohibits a total acceptation of the market efficiency under its weak and semi-strong form.

### 1.2.3 Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) depends on the efficient market hypothesis to predict the relationship between future earnings and the systematic risk of an asset. It was first introduced by Sharpe in 1964 and was built on a previous paper of Markowitz (1952) and followed by further evidence including Litner (1964).
The model is set as:

$$E(R_i) = r_f + \beta_i * [E(R_M) - r_f]$$

where $E(R_i)$ represents the expected return on a security i, $r_f$ is the risk-free rate of the market, $\beta_i$ captures the sensitivity of the expected asset returns, $E(R_M)$ is the expected return of the market.
Thus, $[E(R_M) - r_f]$ is the expected market risk premium.
Beyond the efficient market hypothesis on which the model is built, other stringent assumptions are mandatory for its definition (Sjøberg, 2011).

1. Investors consider a single-period time horizon
2. Investors are mean-variance optimizer, rational and risk-averse
3. There are no transaction costs for the securities' trade nor taxes on earnings
4. Investors can choose between all tradable assets
5. Investors are price takers
6. All purchase and sales transactions are perfectly divisible

The $\beta$ measures the volatility of the security relative to the overall market. Thus, it is defined as the ratio of the covariance of the returns on the securities with the ones of the market by the variance of market returns (Weston, 1975).

$$\beta_i = \frac{CovR_i, R_M}{VarR_M}$$

When the $\beta$ is equal to 1, it points out that the security is highly correlated with the market. A $\beta$ higher (lower) than 1 indicates that the security is more (less) volatile than the market. The total risk entailed by an investor who detains a portfolio composed of a given number of stocks is composed of the systematic and unsystematic risk. As opposed to the **unsystematic risk** that is firm or sector-related and removable by means of diversification, the **systematic risk** is related to the aggregate market and not shrinkable through diversification. Obviously, the market portfolio comprised of all the individual portfolios does not hold any unsystematic risk. From the assumption that one's portfolio is well-diversified and is comprised of a at least 30 stocks (Statman, 1987) only systematic risk should be priced.

The CAPM provides with a seductive simplicity for predicting the returns on risky assets (at the equilibrium). However, the empirical problems arising from the bounding assumptions make it difficult to implement.

## 1.3 Critics of the efficient market hypothesis

### 1.3.1 Theoretical evidence weakening the EMH

Under risk and uncertainty, empirical and theoretical evidences in agents' behaviour disclose a systematic deviation from the EMH. Theoretical divergences were classified in three domains by Kahneman & Riepe (1998).

First, systematic biases of judgments are present in agent's decision-process as he is required to predict without a total control on external factors. That is to say, people violate basic probabilities rules such as Bayes' theorem. There is a systematic failure to stand back

from the situation when new information is released. It leads actors to draw inaccurate conclusions. Indeed, their overreaction to salient information as well as the use of familiar patterns overcome the essential principles of probabilities.

Second, professionals and lay men make errors of preferences in their analysis of financial situations. Kahneman & Riepe (1998) addressed how people manage probability information in this context. There resulted a violation of rational principles, such as Bayes theorem, in multiple ways. Some evidences on the non-linear weighting of probabilities, the valuation of changes instead of states and a redefinition of the value function were presented. The theme of the systematic underweighting of high probabilities and overweighting of low probabilities in an uncertain world will be discussed later in the presentation of the "Prospect Theory" by Kahneman & Tversky (1979). However, a relevant example of this feature given by the authors is people's preference for a 1% chance to gain 1000$ compared to a 10$ gift. They stated that people seemed not to be driven by where they get in the end but rather by the gains or losses of each possible choice. That is to say, the preferences are influenced by the broadness of the decision problem. By this we mean that, an issue being defined in broader terms, e.g. the wealth, results in different preferences - more rational - than the same problem expressed in narrower terms such as changes in wealth. Lastly, two outcomes are pinned out for the value function under risk and uncertainty. The function is sharper for losses than it is for gains. This asymmetry called loss aversion, is essential for the understanding of the pricing of stocks and bonds. This is defined by the authors as the *near-proportionality of risk attitudes.*

Third, the optimisation of financial problems does not take into consideration the emotional consequences for the stakeholders. For instance, people tend to be most badly affected by events assimilated to regrets than resulting of an omission to take the shoot. When the adoption of the bad decision is due to an external advice, the feeling is even more pronounced. Indeed, people think that they should have listened to themselves to have avoided this bad situation.

These are a few from the theoretical results discrediting the assumption of a market made up of rational agents. Although this gives a hindsight on the fragility of the pillars supporting the traditional theories, it is not enough to prove the caducity of the efficient market hypothesis. Accordingly, the EMH does not postulate the efficiency of each individual agent but the cancellation of the deviant behaviour when their number is large. However, this is possible only if randomness in the directions of divergence is observed. The results presented above show that biases reported in agents' decision process seem to be positively correlated as they adopt the same behaviours. This positive correlation is due to the irrational agents, also called noise traders who are mutually influenced and thus deviate in the same direction which feeds the vicious spiral.

### 1.3.2 Empirical evidences weakening the EMH

The theoretical weakness of basic principles supporting the EMH is completed with observations on the financial markets. Systematic anomalies, appearing during stocks and other securities' exchanges support theoretical findings shattering the rationality of the market. First papers gathering empirical evidences of inconsistency between the weak or semi-strong form of market efficiency and price behaviours were released in 1985 by Thaler & De Bondt.

#### 1.3.2.1 Momentum effect

A variety of momentum strategies went through examination by Jegadeesh & Titman (1993) and Rowenhorst (1998) for the US and European markets respectively. They demonstrated significant profits of about 1 % per month for "strategies that buy stocks with high returns over the previous 3 to 12 months and sell stocks with poor returns over the same period". Some authors argue that these abnormal returns are a compensation for the market risk and not an evidence of market inefficiency.

Jegadeesh & Titman (1998) reviewed the results obtained in 1993 and analysed cumulative returns for the 5 years following the formation date of different portfolios. Behavioural

models suggest a reversal in the returns due to a deferred overreaction. Accordingly, as stakeholders neither incorporate information on time nor at the proper magnitude, the price of the best performing portfolios stay above their long-term and fairer value. As a matter of fact, the authors observed cumulative negative returns from month 13 to 60, considered as the post-holding period of the momentum portfolio. Authors discussed several causes to these negative returns and found the most consistent responses in these new behavioural discoveries. Barberis, Schleifer & Vishny (1998) explained this long-term overreaction by combining previous results on the conservatism bias and the representativeness heuristic. On the one hand, representativeness heuristic in agent's behaviour induces them to see patterns in uncertain and non-recurrent events such as a firm experiencing important profits while there is no clue that these substantial earnings will sustain their growth. On the other hand, the initial underreaction is due to the conservatism of individuals.

Hong & Stein (1998) tackle the problem without any direct reference to behavioural biases but converged to the same conclusion. Their paper supports the division of investors in two groups based on their access and treatment of the information. One group has a better knowledge of new information and does not take into consideration past figures. On the contrary, the less informed tracks the past record of prices without analysing the fundamental information to manage their portfolio. Initially, the momentum profits are due to a partial incorporation of the information that informed investors transmit with a delay. Then, technical investors forecast based on a past history that failed to reflect all the information available. This causes the predictions to be upwards-biased. Finally, we observe an outperformance of past losers over past winners when the prices return to their fair and fundamental value causing the direction of the returns to reverse.

Other reasons such as the *self-attribution bias* have been advanced by Daniel, Hirschleifer & Subramanyam (1998). After the holding period, investors tend to attribute satisfying results observed in the returns of best performers comprised in the momentum portfolios to their ability to make right decisions on time. Conversely, their failure to get decent returns

is excused by a lack of luck. This distortion feeds investors' belief that the maintained performance of past winners is due to a good management of the portfolio which tends to push the price of these portfolios to higher levels.

Nonetheless, the authors at the origin of the momentum portfolio' results emitted light reserve about the behavioural justifications of their colleagues. All of them justified scientifically the negative returns post-holding period. However, little explanations over the 48 months post portfolio formation required to see reversal in the returns were found in the literature reviewed.

#### 1.3.2.2 Size and January effect

In *Stocks for the long run* the most disturbing calendar anomaly was documented by Siegel (2006). From 1925 to 2006, big-capitalisation stocks have been significantly outperformed by small-capitalisation stocks in January (64 out of 80 years). During this month, small-caps that annually have compound returns 1.9 % lower than the bigger, revealed returns that exceeded their annual average by 4.5 %. These observations are even more substantial in time of crisis such as the Great Depression. Among the possible explanations of this effect, we can find the US tax-scheme that stimulates the selling of these small capitalisation stocks detained by individual investors in December. This event occurring in December induces an instantaneous diminution of the stock prices. However, the stocks will be traded again in January which induces an increase of the stock prices. The cause of this effect is not the matter of this section. However, it helps us to go deeper in the destruction of a supposed efficient processing of the publicly available information (semi-strong form of market efficiency).

Indeed, all the investors have access to the information that should be embodied in the pattern of the small stocks. If the market was rational under the semi-strong form, this could not happen. It should be emphasized that some changes in the anomaly have been detailed by Siegel (2006). Even if the January effect is still present nowadays, the gap between small- and big- caps returns has been drastically reduced in the 1990s before rising back since 2000. This

could be the result of a better processing of the information by investors, which attenuated the gap. As time passes, investors omit to take into account this anomaly in their predictions and the breach broadens again.

#### 1.3.2.3 Arbitrage

Lee, Schleifer & Thaler (1991) showed the limits to the "law of one-price" for closed-end fund and their underlying portfolios. Different issues were pinned out: the timely adjustment required when the underlying portfolios are changed, or the costs associated to the hedging of the portfolios on their own. This could make the longing of the portfolio with regards to the shorting of the undervalued closed-end funds difficult.

Mitchell, Pulvino & Stafford (2002) studied the impact of the costs associated to imperfect information and other market frictions on arbitrage. To do so, they tracked "negative stub value" situations or cases of companies valued at less than the shares they detained in a publicly traded holding/subsidiary. A textbook case largely diffused and followed in the press is the price relationship between Palm and 3Com shares in the early 2000s. At the time of the IPO, the market capitalisation of the daughter company (Palm) exceeded by far the market capitalisation of the parent firm (3Com). On March $2^{nd}$, Palm was valued at 53.3 billion $ whereas 3Com value reached only 28 billion $ (The New York Times, 2000). In this case, arbitrage implies going long for positions in the parent firm and short for positions in the ownership. By longing positions in the parent firm, an arbitrageur indirectly holds a share of the subsidiary.

The termination time was defined as the period between the initial mispricing and the breakup of the mother/daughter firm's bond.
They highlight that for their sample (82 situations between 1985 and 2000), the termination time ranges between 1 and 2796 days with an average of 236 days. There is a risk that

the rupture of the relation between the two companies happens before the mispricing has been eliminated since the termination event is hardly predictable. This is defined as the fundamental risk that the trader who would like to take advantage of the situation is running. Moreover, arbitrageurs are prone to this financial risk since the way to convergence (when it occurs) is not a long calm river. The longer this path is, the higher will be the horizon risk as the negative stub value could be ended before its term.

Arbitrageurs face several risks and high costs due to the imperfect distribution of the information. That is to say, these barriers reduce their scope of action and prevent them to push stock prices to their fundamental value. However, the efficient market hypothesis considers the action of these individuals as primordial to regulate the market. The destruction of this argument jeopardises severely the framework used by classical finance theories.

# 2 Behavioural Finance

The efficient market theories fail to provide enough answers when dealing with markets that are not behaving rationally. Behavioural finance is meant to analyse markets when assuming that the latter are not fully rational as specified in the traditional finance theories. This branch of modern finance takes into consideration the psychological dimension and is built according two mains axes: cognitive psychology and limits to arbitrage.

## 2.1 History of behavioural finance

The traditional market theories failed to provide enough answers to the anomalies on the financial markets. In this context, behavioural finance has emerged. Intuitively, the presence of market anomalies that have failed to be explained by the theories previously described prove that the processes to which agents refer when deciding are not transparent as classical theories claimed. As early as 1630, irrational events such as the *Tulipomania* could have aroused the suspicions of the ones defending the rationality of the agents involved in the market.

The first documented speculative bubble in history stayed in the memory and is now a classic that every economics student heard about. During this episode, infected tulips gained in extreme popularity for their colourful petals. However, tulips are only harvestable during a certain period. As the market of tulips grew in popularity and occurred a disequilibrium between offer and demand, people started to contract at term broken bubbles. In 1636, speculators learned about the opportunity and came into play provoking tremendous daily exchanges of those bubbles. However, none of these deliveries was possible to be achieved due to the turning ratio of these speculations. At its peak, a single tulip bubble was priced 10 times the monthly salary of an artisan. In February 1637, a buyer who failed to honour his contract caused the market to abruptly fall. All the ingredients for a crisis were reunited:

sellers tried massively to get rid of their positions while buyers had disappeared. The vain attempts of the Dutch government to redress the market did not more than frighten the stakeholders, resulting in an economic depression for several years.

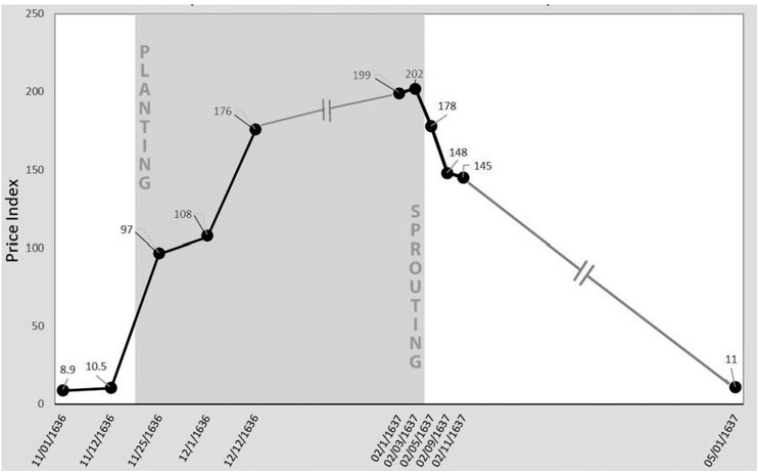



**Figure 1:** Prices of Dutch tulip bulbs, 1636-1637

What happened during this obscure event was the result of **positive feedback strategies**. As one knows, the profits made by speculative investors on different products may inspire their less informed pars who seek this financial success. As the information is transmitted among agents, euphoria gains the markets. Investors buy the products, causing their prices to skyrocket. With regard to the irrationality at the origins of these movements, the current level of prices cannot be sustained to this level. In general, word of mouth tends to promote a certain class of assets with hardly evidence of their profitability. Thus, the speculative bubble does never take long to burst as the market realises the dangerous situation where it has landed.

Later, experimental evidences confirmed the feedback theory that has initially emerged in popular discourse. Research in psychology as well as empirical studies permitted to manifest evidence that human judgements were subject to systematic biases.

A few pioneers namely Leon Festinger, Henry Riecken & Stanley Schachter contributed to the

birth of behavioural economics in the first half of the $20^{th}$ century, by proving experimentally the bounded rationality in decision making.

However, it was not until the late 1970s that the major discoveries were disclosed. The emergence of this discipline was fostered by the anomalies resulting in the use of traditional theories that leaded to different crisis. Conclusions of psychologists and field professionals on the rationality of the agents and the axioms associated are considered as the starting point of the discipline. Some of their discoveries on the reprensatiteveness heuristic are central in the understanding on how an operator diverges from the rational agent.

*A prospect theory: An analysis of decision under risk* by Kahneman & Tversky (1979) is considered as the fundamental research questioning the effectiveness of the expected utility theory. The two psychologists, later supported by several economists, proved that the attitude towards risk was not only determined by the **utility function** but by two parameters v and pi, jointly forming the **value function**. Thus, they proposed "The prospect theory" modelling the attitude towards risk while taking into consideration other aspects that had been previously omitted. This alternative method considers the **non-uniformity of the risk attitude**, meaning that not all gains and losses are felt equivalently, the **loss aversion** of the economic agents and the use by the individuals of a **reference point** to value the prospect of a decision. These findings combined with the use of psychological biases reformed the conception of rationality to a decision-making process influenced by the subjectivity of the individual (Schinckus, 2009).

De Bondt & Thaler (1985) in "Does the stock market overreact?" linked the anomalies observed in the stock market with the hypothesis of individuals' irrational behaviour. They assumed that this discrepancy had its source in an overreaction to the information released to certain actors.

From the 1990s, the terms "behavioural finance" are institutionalised and numerous seminaries and other conferences were held. The researches of De Bondt & Thaler (1990) and

Jegadeesh & Titman (1993) go in the direction of the feedback theory and show the persistent inconsistency of the presumed random walk. Indeed, they displayed that stock prices tend to continue in the same direction over intervals of 6 months to 1 year but to reverse over the long run. The pillar of the random walk and in general the classical finance theories was the alleged perfect reflection of all the information available in the market prices. This was caused by a belief of an impossibility for market prices to systematically deviate from the fundamental values as underlined by Fama (1965). As these beliefs are based on the hypothesis of the rationality of the entire market, the theories lost most of their accuracy due to this huge shift.

These gatherings allowed a homogenisation of the research practices that were until then empirical studies mainly conducted in an uncoordinated manner. The proliferation of behavioural finance articles allowed on the one hand to broaden the community of economists querying on the causes of the irrationality of the market. On the other hand, it helped stabilising the foundations of this new school of interpretation in finance. Less than a decade later, at the end of the 1990s, the first periodic publications totally dedicated to this science were created. Their purpose was to promote an interdisciplinary research directly inspired by cognitive sciences.

The schema ruling the critical thinking of these cognitive theorists follows a simple pattern. They identify the heuristics simplifications that control agents' behaviour and interfere in the decision-making process.

## 2.2 Heuristics simplifications

### 2.2.1 Anchoring

This phenomenon can be considered as a subject's inclination to develop his reasoning process either from an initial point previously estimated or under the influence of the formulation of the problem. Indeed, in situation of uncertainty, people tend to base oneself on figures

without any proof of their relevancy. As showed by Englich, Mussweiler & Strack (2005), experts are also prone to this cognitive bias. Their empirical study tried judges who were asked to roll dices and sum them and to later issue a sentence. Even if these judges were aware of the irrelevancy of the number, they found in the first part of the experiment, the group with the higher sums gave an average sentence significantly higher.

Epley & Gilovich (2006) went further by demonstrating that not all anchoring effects derive from the same psychological process as previously thought. Indeed, the research found that anchoring could be altered by manipulations of subjects' ability or consent to devote themselves to the task since adjustment is considered painful. Insufficient adjustment happens when the person reaches a result from an incomplete computation after having started from an initial value given. That is, people stop the process of adjusting as soon as they find a plausible value comprise in a range that they had predetermined. This is due to the process they see as painful and for which they don't want to dedicate themselves. Other studies showed the tendency of people to overestimate the occurrence of conjunctive events and underestimate the occurrence of disjunctive events as a result of this heuristic. This leads us to excessive optimism when the success of a certain event is conditioned by the success of a sequence of other steps. Indeed, even if the completion of the previous steps seems straightforward, their large number decreases the probability of occurrence of the final event. For reducing the anchoring effects, it is important to inform about the bias while providing stimuli to increase the accuracy (Epley & Gilovich, 2006).

### 2.2.2 Representativity

Individuals typically suffer from representativeness heuristic when they are asked to evaluate the probabilities of some events to occur. That is, they often make forecasts based on information that not affects sensibly the result to be predicted due to the simplifications they tend to make when they observe similarities. Representativeness issue can be separated in 6 components regarding the type of issue leading to misinterpretation of the information

provided.

First, there is a confusion between what influences representativeness and probabilities. When they are subject to this type of heuristic, people forget to take into consideration prior probability when they have access to irrelevant information. Kahneman & Tversky (1974) resumed this feature "When no specific evidence is given, prior probabilities are properly used; when worthless evidence is given, prior probabilities are neglected".

Second, an insensitivity to sample size was highlighted. People evaluate the likelihood of obtaining a sample result by its similarity to the population parameter. Intuitive judgments are affected by the sample proportion and not by the size of this sample. A misconception in the chances was also observed as the results found in small samples are too often taken as representative of the whole population.

The individual decision-process is influenced by the favourableness of the description mobilized to predict outcomes and the reliability of the source does not play any central role. This implies a violation of basic principles on the shape and extremeness of the curve of predictions. That is, "Prediction of a remote criterion was identical to the evaluation of the information on which the prediction was based". This is known as the insensitivity to predictability.

The illusion of validity refers to the selection of an outcome for its better match with the input and results in an unfounded confidence on the quality of one's prediction. The consistency of this illusion is still proved when the subject is aware of the limited accuracy due to the factors on which he relies. Moreover, a higher redundancy or correlation in the parameters increases wrongly this feeling. Statistically, better qualities of predictions are achieved with independent inputs.

The last possible cause of representativeness explained by Kahneman & Tversky (1974) is related to an unfair conception of regression. This regression fallacy occurs when one mistakes the statistical phenomenon of regression to the mean for a causal relationship. The persistence of this phenomenon is even more pronounced when the correlation between two measures is imperfect. Galton (1907) first described that when a random variable is extreme

in the first measure, it will tend to get closer to the mean on the second one. That is to say, special performances are often attributed as the effect of an action when it would have happened anyway. To counter this event, setting up a control group is a solution. However, this implementation becomes difficult in reality for evaluating the performance of a certain policy as no clue of the effect without it can be found.
This tendency to find patterns where only random series are present might lead to overreaction. Investors tend to overestimate the probability of an event that occured recently

### 2.2.3 Availability

Availability could be a good proxy to evaluate the frequency or probability of an event because usually examples that have great chances of happening come easily in mind. However, one judgmental process is parasitized by systematic errors. For example, the retrievability of examples is affected by the salience, the familiarity or the freshness of the factors we could hang on to for evaluating the occurrence of the result. Other factors such as the "effectiveness of a search set" or the "imaginability" were added by Kahneman & Tversky (1974).
Chapman & Chapman (1969) defined the illusory correlation as "a systematic error in reports of observations of a supposed correlation between the occurrence of two classes of events". This incorrect association arises when we accentuate one of the outcomes without correct consideration toward the others. This makes us linking events that are only weakly or not at all connected. Ernst, Kuhlmann & Vogel (2019) evaluated contingency judgments in the rating tasks of different stocks and found that illusory correlation surfaces when the majority and the frequent outcome are associated.

### 2.2.4 Conservatism

Conservatism is considered as an ego defence mechanism and describes the tendency of remaining on your positions for too long before slowly adjusting from them (DrKW Macro research, 2005). It originates from one's trend to over evaluate the value of information

confirming his opinion in comparison to the ones infirming it. This bias intends to promote historical information to the detriment of new one.

To show the effect of the conservatism bias on the asset prices, Luo (2014) first classified traders in three groups: rational, conservatism and noise traders and considered the competitive market as composed of risk free and risky assets. Depending on the calibration of the parameters chosen, good news which are news inducing a better yield than the expected payoff, result in over or under-reaction. More on this subject will be detailed later.

### 2.2.5 Familiarity

This heuristic occurs when an individual favours an option over another because the first is more familiar to him than the second one. As a matter of fact, Heath & Tversky (1991) showed that people preferred betting on "their vague beliefs over a matched chance event". For some investors, this generally implies sub-diversification in the management of their portfolio since they promote a small number of companies because of their presupposed familiarity.

Sercu & Vanpee (2007) reviewed recent empirical findings relative to the home bias puzzle. The home bias is defined by the authors as the "overinvestment in domestic stocks relative to the theoretically optimal investment portfolio". The local bias refers to the same inclination of the portfolio towards local assets instead of national ones. Then, they investigate both institutional and behavioural-based arguments to this heuristic and found that the puzzle was the result of a combination of both types. Explanations based on institutional factors: hedging domestic risk by investing in home-country assets, costs relative to foreign investments, information asymmetries between national and external investors or corporate governance and transparency and political risk failed to capture all the issue addressed.

That is, behavioural explanations associated to the representativeness heuristic previously described bring another angle for the resolution of this puzzle. Investors perceive unproven higher level of risk in foreign markets. Thus, they are adapting the distribution of their returns with regards to their better relative perceived competency in the home-market.

The magnitude of this bias widens with the level of overconfidence of the investors; the higher it is, the more upward is their overestimation in their ability to determine stocks' performance in familiar markets.

Moreover, the study showed greater presence of this cognitive bias incidence for home-investors operating in developing countries where the stock market is more volatile than in developed countries.

## 2.3 Emotional biases

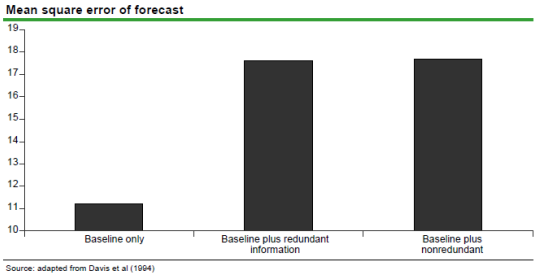
### 2.3.1 Overconfidence and self-attribution

Soaring degree of trading are due to the overconfidence of the investors. (Barber & Odean, 2001) tested overconfidence using gender as a proxy variable and found heterogeneity regarding abilities and knowledge leading to consequences for the performance of each group. It has been previously demonstrated that men were more overconfident than women and the authors provided the link between this finding and the poorer trading results of the male gender. The study conducted on 37,664 households shows that their excess of confidence incites them to trade more, reducing their net returns by 2.65 % while this reduction reaches 1.72 for the female counterpart. The costs associated to the high frequency of trading are the reason of the lower returns while there is no statistically significant difference in the purchase performance of the two groups.

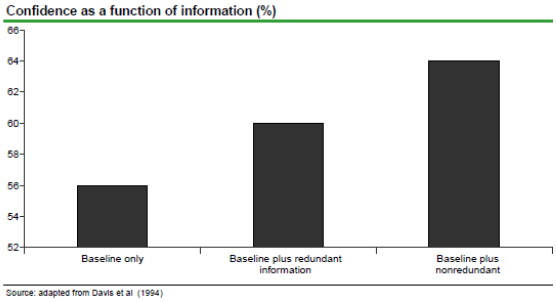
Many investors believe that more information is better information and adopt a behaviour that is consistent with the EMH. For them, the only way to defeat the market is to know more than the average by an endless query for information. Davis, Lohse & Kottemann (1994) conducted a study concerning how earnings forecasts were impacted by information. Students on an MBA course were asked to forecast the fourth quarter earnings of 15 different companies. However, each of them was presented in three different formats without the participants knowing it. The first set included information concerning net sales, stock price

and the past three quarters of earning per share. The second and third set included the first set of information to which was added respectively redundant and non-redundant data about the company. Then, the accuracy of the forecasts was calculated by computing the mean square error. As information is added, relevant or not, the error of forecast increases meaning less accurate predictions. Regarding the confidence in their forecast, the investors are even more sure of what they advance when non redundant information is provided.

Dealing with more information worsens the forecasts that are delivered while it tends to make us feel that we are predicting more accurately. This generally implies too little diversification.




**(a)** MSE as a function of the information




**(b)** Confidence as a function of the information

**Figure 2:** Influence of the quantity and quality of information

Professionals more than lay men are subject to this bias. In most tasks, they show a significant higher degree of overconfidence than the student control group. Glaser, Langer, & Weber (2005) tested various forms under which it could be manifested and their correlation.

The authors tried the correlation between the three different manifestations of overconfidence

previously detailed. They find that the better than average effect and miscalibration were not related as they had insignificant correlation coefficients. Further, they showed that experts are biased even when computing real time series forecasts.
Furthermore, the results regarding the stable individual differences within tasks support the hypothesis that investors can be classified regarding their degree of overconfidence.

#### 2.3.1.1 Miscalibration

Miscalibration is defined as the "systematic underestimation of the range of potential outcomes" (Ben-David, Graham, & Harvey, 2013). It results from an excess in the confidence about the accuracy of the information we detain. In this context, people either overrate the precision of their predictions or underrate the fluctuation of risky processes. The authors sort subjects depending on either their optimistic or miscalibrated characteristic and establish the link between these concepts.
Once a quarter and over a 10 year-period, US CFO were asked to provide forecasts within a 80% confidence interval about their 1 and 10 years forecasts on the 1st American market index. The results are stringent: the realized 1 year returns of the SP 500 lies 36.3% of the time in the interval provided. Most of the time, the confidence interval estimated are too narrow regarding the volatility of the situation. If in period of crisis, they try to slightly adjust by enlarging these intervals, the compensation is far from being enough leading to predictions even less calibrated.

#### 2.3.1.2 Better than average effect

The above-average effect occurs when the greater majority assumes that their abilities or personal skills are better than half of the population. However, a distinction has to be done between apparent and true over placement. It is not enough to show that people place themselves above the others to prove overconfidence. Rational over placement is possible if and only if the agents don't know to which type they belong with certainty. Benoit & Dubra

(2011) relied on the Bayesian rationality to demonstrate this assertion. Bayesian rationality defines the ability to reason about uncertainty as the true rationality. In this setting, the non-acknowledgement of their own types by the subjects is primordial.

Proof: Let's say x is the portion of the population believing they are in the upper half of the distribution with a probability $p > \frac{1}{2}$, then Bayesian rationality implies that $x * p \leq \frac{1}{2}$ not that $x \leq \frac{1}{2}$.

Therefore, the authors concluded that weak tests composed of closed questions such as "Do you think you are better than half of the population?" failed at establishing overconfidence. Stronger tests where the subjects are asked to deliver specific probabilities estimates neither fill the gap. Thus, the portion of people who place themselves above average do not measure well the degree of true overconfidence.

If measuring well the degree of true overconfidence revealed not to be easy to prove, the source of this phenomenon is well known. The overriding tendency to rely on private information can involve at short term positive autocorrelation between one's behaviour and the situation. For example, when investors decide to overbuy a certain asset class, it is undeniable that its price will skyrocket. However, if the public information goes in the opposite direction, the movement of the prices won't last to reverse, leading to a negative correlation with investors' behaviour and abnormal prices' movements.

#### 2.3.1.3 Illusion of control and unrealistic optimism

The illusion of control refers to the feeling that one's behaviour exerts an influence over outcomes over which they have limited control (Yarritu, Matute, & Vadillo, 2013). When investors view the results as predictable, their outlooks are more optimistic and the higher the sensation of control over the performance is, the higher their optimism tends to be (March & Shapira, 1987).

To explore the managers' illusion of control, Hsu & Chen (2017) used as a proxy the increase in the ratio of capital expenditure as short term non-recurring surplus increases. Companies'

operating risk depends on its non-operating income and expenditures. The results showed that these two elements had a lagged significant positive impact on the future expenditure ratio. This supports the previous studies stating that a manager's optimistic vision enhances the dependence of capital expenditure to cash flows.
The perception of control with regards to earnings is significantly more pronounced than for the prices. The valuation of stock prices requires long term discounting of the present and future earnings. The risk premium is embodied in the discount factor and depends on several factors that are not controllable such as the subjective perception and pricing of market participants. This non-transparency reduces the feeling of control.

There is a strong relationship between overconfidence and the momentum effect. Overconfident market participants reflect in their predictions the private signals that they have perceived with too much weight. That is, people tend to overreact to private signals and underreact to public signals.

### 2.3.2 Framing

Agents adopt distinct decision-making processes depending on the terms of presentation of a problem. This process is influenced by the context. When highlighting a different reference Kahneman & Tversky (1996) showed that the presentation of a problem in negative terms, tends to influence an operator's behaviour through risk aversion. On the contrary, when it is described in positive terms, he is risk seeking. This partly explains why volatility increases when the markets are plunging. As the agents localize their situation at a loss, they augment their exposition to risk.
Wang (1996) introduced a distinction between bidirectional and unidirectional framing. Bidirectional framing refers to the reversal of the preferences while unidirectional framing relates only to a shift of preferences. This process is directly linked to mental accounting where by "investors may segregate accounts or monies and take risks with their gains that

they would not take with their principal" (Nguyen, 2018).

E.g. Let's take a very simple example to illustrate these assertions. When it comes to investing, people and even experts tend to split the portfolio into a secure part and a more speculative one. Unsurprisingly, the net wealth would not have been affected if both portfolios had been merged into a single one. The issue resulting is that the investor could be tempted to reduce the allocation of the winners in the riskier portfolio to increase the safety of the other. However, the equilibrium sought is severely impacted by one's tendency to keep winners and sell losers. This could be the reason why mutual funds are well considered. In the mental accounting setting, they have a certain efficiency because losses are virtually offset by gains to provide an overall yield.

## 2.4 Market anomalies

### 2.4.1 Herding

The herding behaviour refers to how individual decisions are affected by group attitude. Wermers (1999) resumed the four explanations for this behaviour in the fund sector most commonly accepted in literature. Fund managers may prefer to mimic the behaviour of their pars while giving less consideration to their private knowledge to avoid the risk of being blamed. Another reason is the very likely possibility that managers have similar access to private information. Thus, they analyse the same figures and draw similar conclusions. The third reason evocated relates to the tendency for managers to try to figure out the information detained by the better informed. Thus, they review sources of information of the formers and adopt the same patterns. The final reason refers to the aversion of particular types of investors to classes of assets for matters of liquidity or volatility (Falkenstein, 1996).

### 2.4.2 Seasonal anomalies

Calendar anomalies are referred as significant changes in the behaviour of stock prices attributable at some point of the year (Rossi, Marcarelli, Ferraro, & Lucadamo, 2020). The most documented calendar anomalies are the January effect that was previously described, the weekend, Holiday, the Halloween and the intraday effects.

#### 2.4.2.1 Weekend effect

This anomaly refers to the recurrent lower closing prices on Monday compared to the closing prices of the preceding Friday. No single explanation to this phenomenon has been consensually reached in the economic literature (Hai-Chin, 2011). However, authors proved that this phenomenon was the result of the tendency to release bad news on weekends (Fishe, Gosnell, & Lasser, 1993). The closing price on Monday includes the information released after the closing on Friday as well as the different events that occurred during the weekend. That is, the objective comparison of Friday versus Monday is highly sensitive. Another explanation for the causes of this behaviour is related to the informal schema followed by investors for their buy-sell decisions. Usually, investors receive "buy" recommendations during the week and are more likely to devote their time for thinking about their "sell" options during the weekend and then sell on Mondays. Most recent investigations pointed out that the anomaly was still present in small-cap firms while there was a tendency for the reverse effect for large firms' securities.

#### 2.4.2.2 Holiday effect

Pre-holiday effect alludes to the abnormally high returns occurring before public holidays. Previous works considered the "holiday euphoria" as the cause of the anomaly (Marrett & Worthington, 2009). Investors would tend to buy shares due to the positive feelings arising before a break-day (especially before Christmas and May day).

Recently, the authors investigated the presence of the holiday effect over a 10 years period (until 2006) in the Australia market and found that returns before holidays were on average 5 times greater than for regular days. However, the effect is mostly observable in a specific sector and only for small-caps. Some reasons evocated to the lower salience of the holiday effects is the increase in institutional investments that results in smaller discrepancy regarded to individual investing that is more volatile. Both for the weekend and holidays effects, the improved access to continuous information plays a paper in the weakening of the calendar anomalies.

#### 2.4.2.3 Halloween effect

To test the Halloween effect, Arendas, Malacka & Schwarzova (2018) reviewed the Halloween effect on 35 major stocks of the Dow Jones Index for the period 1980-2017. This anomaly is defined as the significant higher performance during the months comprised from November to April than for the other half of the year. Lloyd, Zhang & Rydin (2017) showed that the effect was still persistent after the 2008 crash supporting the results of Arendas et al. (2018). The panel studied by those showed a stock's price behaviour consistent with the Halloween effect more often than not and that average returns from November to April are significantly higher than for the May to October period.
Similar conclusions for the European stock market were highlighted by Carrazedo, Dias Curto & Oliveria (2016). The authors set a successful trading strategy on the basis of this anomaly beating the simple buy and hold policy 80 % of the time.

#### 2.4.2.4 Intraday effect

Intraday effect refers to the recurrent patterns that implies more aggressive trading at the opening and closing of the trading day which results in a higher volatility in the prices (Admati & Pfleiderer, 1988). Khademalomoom & Narayan (2019) considered the intraday effect in the foreign exchange market over a 10 years period covering the global financial

crisis. They showed that setting a trading strategy based on the moment of the day was profitable. Indeed, the currencies returns were most impacted at certain points in the day i.e. right after the local market opens, at the opening and closing of biggest markets and during overlapping trading hours.

## 2.5 Black swan events

Generally, an event is defined as a black swan when it has a "very low probability of occurring but with potentially dramatic consequences". We found interesting to include this section as black swan events recently gained interest with the COVID crisis. The popular definition of this type of events claims that black swans include all events with a low probability, a high impact and that could be considered as predictable retrospectively. As stated by McGillivray (2020), qualifying the recent crisis as a black swan is dangerous if all aspects of this type of event are not totally understood. Indeed, the ones who could have do some damage control might be tempted to use it as an excuse to clear their own responsibility. As wisely summarised by the author "With pandemics, it is not really a question of if, but usually when". Under this assumption and following his own definition, McGillivray refuses to consider the COVID-19 as a black swan. In the following section inspired by Aven (2013), we explore the four possible axes of definition of black swan events and we will see how it is possible to better include them in the forecasts.

### 2.5.1 The event given its expected occurrence rate and consequences is surprising and extreme

The first case advanced by the author is the following: an extreme event that happens on average every 100 years. If we consider a Poisson process (with a parameter $1/100$ then) and a period of 10 years, we would approximately have a 10% chance that the event will occur during this period. Some events are rarer and could have a probability of occurrence of let's

say 1/100 000 and thus the chance of occurrence over our period plunges to 0.01%. That is, the individual probability that will occur stays very low. In practice we are exposed to many event processes and this rapidly increases the chances that at least one of these processes will occur. However, we don't know for sure all types of extreme events to which we are exposed to, and their frequency.

### 2.5.2 The event has very low probability and extreme consequences

Here, there is a difference with the view exposed in the previous explanation. Lindley (2008) assumes in its hypothesis that we are facing a large sequence of independent trials, each of them having the same distribution (uniform) and the same chance of success. In this context, a black swan event will occur with certainty as equal to zero. Nonetheless, the qualification of an event as a black swan based on a unique analysis should be treated lightly as the certain event could be grouped in the same category as other similar ones.

### 2.5.3 The event given its expected occurrence rate and consequences is surprising and extreme even in situations with large uncertainties

To investigate this hypothesis, a comprehension of both epistemic and aleatory uncertainties needs to be done. When it is known that a parameter will take a value or another without knowing exactly which value it is, we talk about epistemic uncertainty. This type of situation refers to a lack of knowledge. Aleatory uncertainty is due to the random process as we know with precision the outcomes possible.

Dubois (2012) discussed these two different conceptions of uncertainty and declares that the weight assigned to each one should be clearly determined. On the one hand, incomplete information can be reduced by a better treatment and gathering of available data. On the other hand, variability needs to be handled with some focused reactions. The identification of both is necessary to make possible the construction of joint probabilities distribution and avoid the subjectivity arising from a unique probability distribution. However, the epistemic and

aleatory forms are not mutually exclusive even if they mobilize different cognitive processes. To understand the role of both types of uncertainty in the decision making-process Fox & Ülkümen (2011) summarized the key characteristics of each one. Some authors before them have released papers for discerning the types of uncertainty based on different features: the type of reasoning, the source of uncertainty of the event or even both (Kahneman & Tversky, 1982). For the purpose of this study, the attribution of uncertainty will be more detailed as the other factors don't seem relevant to conduct our research. The authors proposed to observe the betting behaviour for determining this attribution. Holding aleatory uncertainty constant, the disposition to bet decreases as the epistemic uncertainty increases. People would rather bet on the outcome of an event before its occurrence than after (the event has occurred, but they don't know more on it than in the first case). That is, the importance of epistemic uncertainty after the event has happened is higher.

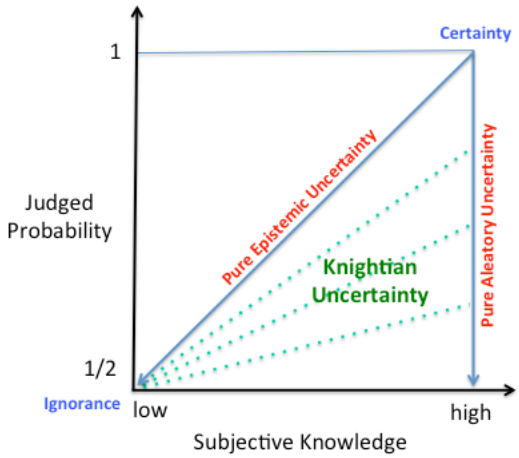



**Figure 3:** Two dimensional framework by Fox & Ülkümen (2011) to characterise uncertainty

The graph depicts that epistemic uncertainty is represented by the perception of one's knowledge whereas judged probability is mobilized to assess aleatory uncertainty. Aven (2013) discussed the notion of the precautionary principle. This method applies when "the consequences of the activity considered could be serious, but we do not fully understand what could happen". When the probability model in itself lacks consensually of consistency and

does not permit a correct understanding of the situation, there are scientific uncertainties. Notably, this occurs in situations where the decision stakes and both types of uncertainties are important. In this setting, black swans happen mostly in this type of circumstances.

#### 2.5.3.1 Hindsight bias

The hindsight bias refers to the retroactive characterization of an outcome as more predictable than it actually was before the event occurred. This error is salient when one has to find deterministic causes to an event or when the process of causal attribution is not well defined. In these situations, the agent will try to find potential explanations in the epistemic dimension of uncertainty.

Roese & Vohs (2012) who qualified this effect as the "knew it all along" distinguished between three levels of hindsight biases. The first hierarchical level occurs when an individual is driven to recollect some past predictions and the latter are distorted towards the seen outcome. This is known as **memory distortion** or "I said it would happen". The second level, **inevitability**, refers to the tendency to conclude that an event had to happen whatever the decision one would have opted for. This feature is built on the first level and is a brick for the next level. On the third stage of the pyramid, is the subjective self-evaluation of one's capability to foresee or in other words, **foreseeability**. Different categories of inputs support each floor of the pyramid from cognitive based to motivational even if the levels are interconnected.

They added that the difference between knowledge learned as a result of a mistake and the bias lies in the timing of the measures taken. If the conclusions are mobilized to forge ahead while avoiding the past errors, this is knowledge driven. Otherwise, when it is only used as a retrospective way to blame a decision maker at a certain point in the past for example, we are dealing with pure hindsight bias. Obviously, from the hindsight bias arise some collateral consequences namely overconfidence and myopia. Myopia is defined as the "exaggeration of the importance of a single explanatory factor" and is mostly an effect of the inevitability and foreseeability dimensions.

Overconfidence has previously been described and is in a nutshell an "unjustified certainty regarding predictions meaning that there is a gap between subjective and objective knowledge/capability". Foreseeability, more than the other components, plays a role in this upward assessment of one's ability. Thus, it induces an unwillingness to rethink unfitted decisions. This is translated in financial decisions by poorer returns for investors who are most exposed to this bias (Bias & Weber, 2009).

Lastly, the paper proposed to rely on two methods to lessen the bias. First, **"consider-the-opposite"** that implies pushing someone to reverse his natural tendency to be trapped in the "I knew it all along" error. This is done by asking for some explanations on how some event that did not take place could have. The second rely on the expertise and tackles principally the **memory distortion**. Indeed, experts show a better ability to recall their previous predictions and in theory provide with better forecasts which decreases the necessity to use such biases to justify one's errors.

### 2.5.4 An unknown unknown

"Unknowns unknowns" refer to a type of events that was not specified in the former risk assessment but still has a major impact. In this setting, a black swan could be considered as an "unknown unknown" because it wasn't taken into consideration in the knowledge background used to make the prediction

### 2.5.5 Conclusion on the black swans

The author concludes on these four interpretations by the definition of a black swan as a "surprising event relative to the present knowledge". Taleb (2007) sets up a framework which clearly supports the view of Aven (2013) regarding the importance to modify the risk assessment process further than the probabilities that were until this point used. Thus, this involves a better definition of the level of knowledge we are basing our prediction on.

The black swan events that occur with a very low probability and devasting consequences are

critical when making forecasts. Indeed, financial analysts who are computing the predictions need to be aware of these possible events and to quantify their consequences. For that, a very good understanding of the different types of uncertainties and how to reduce one's hindsight bias is mandatory.

## 2.6 Analysts' forecasts

### 2.6.1 Who are the financial analysts?

A financial analyst is a person mandated to make predictions about the future performance of a company, sector or an industry. They gather evidences on the micro and macroeconomic levels to provide these forecasts. These analysts are divided in two groups: "buy-side analysts" and "sell-side analysts". Only sell-side analysts release publicly available reports containing predictions for some key financial elements (quantitative and qualitative) of the companies.

### 2.6.2 What are the target prices?

Target prices are included in the financial analysts reports and alongside the predicted earnings per shares (EPS) and stock recommendations represents easily verifiable elements of the reports. They offer straightforward material to the investors, more easily interpretable than the EPS. However, the interest for the target prices in the literature is very shy compared to the two others key financial elements previously cited. Rogers & Grant (1997) examined the sources of information used for 187 sell-side analysts' reports. They demonstrated that about half (51%) of this information came from the annual reports. The other figures are from sources external to the company's financial and operating reporting.

Analysts' reports are the principal mean of communication between the managers and the investors and enhance the information symmetry. Thus, analysts tend to emit reports for companies where stakeholders will largely use their work. That is, big-cap companies whom investors' demand of information is high due the number of shares exchanged and the liquidity

of these stocks (Bonini, Zanetti, Bianchini, & Salvi, 2010).

Until Bilinski, Lyssimachou, & Walker (2013) most of the researches on the accuracy of financial analysts' forecasts were targeting earnings per share. However, as said in the chapter related to the perception of control, the valuation of future prices requires more judgment. Indeed, they include analyst' considerations on the long-run risk and the returns associated. Bilinski et al. (2013) observed that the accuracy of the target prices was increased as a function of analyst's experience, the size of the brokerage firm employing them, the number of companies they cover, and their expertise of the country's market. In addition, lower historical target price error foresees better contemporary target prices' accuracy. This had been previously showed by Clement (1999). On the one hand, the accuracy of the forecasts is based on the abilities and characteristics of the analysts and the broker firms that employ them.

On the other hand, part of the quality of the target price results from the informational efficiency. A significant correlation between the institutional factors and the accuracy of the forecasts has been established. Countries where the clarity of accounting standards is higher show more accuracy in the forecasts delivered on their market. Other institutional and regulatory factors such as the corporate model of governance in place in the country have an impact on the quality of the forecasts. In their model, Antonio et al. (2017) capture these countries- specific features into a single variable named "Government effectiveness".

### 2.6.3 Accuracy of the target prices

Bilinski et al. (2013) tested the hypothesis of better predictions by analysts than for "simple price forecasts". Naïve investors would compute the latter by extrapolation of the historical stock price performance. That is, for computing the future stock price one year ahead (12 months horizon as the target prices computed by analysts) they increase the actual stock price by the same growth percentage as observed over the past 12 months. The authors showed that analysts' accuracy in the forecasts was 9.2 % higher than the "simple price

forecast" method.

Bonini et al. (2010) provide evidence on the degree of accuracy for the target prices issued on the Milan Stock Exchange. They acted as pioneer for the research in this field since very few papers on non-american markets had been released before.

A systematic upward bias is empirically supported by their results and by the features of the forecast errors: significantly and consistently greater from zero, autocorrelated, and non mean-reverting.

The degree of research has a negative impact on the accuracy of the predictions while the degree of consensus regarding the future earnings per share is positively correlated to the accuracy. The results linked to the research intensity were contested by Kerl (2011) who shows that the more detailed were the reports, the smaller was the forecast error.

Vlah Jeric & Andelinovic (2019) evaluated the predictions of local market players (not only financial analysts) regarding their national index value, the CROBEX. Their results showed an irrationality in these predictions due either to inefficiency or biasedness and in some cases both. These conclusions were drawn from a definition of the forecast error borrowed to Davies & Lahiri (1995). In the latter, three dimensions are considered: the individual bias, the shocks and the idiosyncratic errors. The difference between the two latest components lies in the possibility to be eliminated or not if the forecaster capabilities are improved. Davies (2006) enhanced the model by authorizing the comparation of different forecasters and horizons. This precaution aimed to capture potential variation in the biases across individual predictors for different horizons that could be mutually offset resulting in an insignificant overall bias. Indeed, Vlah Jeric & Andelinovic (2019) claimed that "the overall bias can partially mask the bias variation with a horizon". The panel of market participants who took the tests showed significant disparity among their individual forecast errors. The study further showed the different impact of shocks compared to "anticipated changes" on CROBEX's forecasts. As a result, the level of disparity among predictors is directly linked to the higher volatility of the shock considered at a certain point in time.

### 2.6.4 How biased is analysts' behaviour? Principal biases and implications

#### 2.6.4.1 Over-optimism

Lim (2001) proposed to establish the relation between on the one side some relevant characteristics of financial analysts and the company and on the other side the forecast bias. For that, the quarterly earnings forecasts from over 300 brokerage firms on the period 1984 to 1996 were reviewed. Adjustments on the data to be analysed were carried in order to remove extreme predictions and outliers due to some features predetermined: stock price smaller than 5$, large discretionary charges, strong relationship between the brokerage firm and the company.

The positive and predictable biases observed in earnings forecasts is not evident matters of the irrationality of the analysts. Indeed, the paper assumes that the predictions are provided in order to minimize the expected squared error. This error is the sum of two components. The squared bias and the forecast variance that can be reduced by a better access to management's private information. That is, analysts have the incentive to deliver optimistic forecasts if they aspire to keep their privileged information source. Thus, this can be considered as a rational bias (Rogers & Grant, 1997).

De Bondt & Thaler (1985) studied how the earnings forecasts produced by financial analysts were subject to overreaction. Exposure to this pattern affects stock market professionals since the forecasted changes are too extreme to be rational. They argued excess returns to losers had to be explained by biased expectations or in other words past overreaction. Previous work on cognitive processes at the origin of biased forecasts (Easterwood & Nutt, 1999) indicates a significant underreaction to bad news and overreaction to good news. This induces systematic upward-biased forecasts.

Empirical evidence in Lim (2001) showed that the bias is more apparent for analysts having strong incentives to be in good relations with the direction when the informational environment is fuzzy. This mainly happens in situations related to two types of events. First, when

the size of the company is moderate and the number of analysts covering the forecasts is reduced. Second, when the company has recently poorly performed (underreaction) or when the management foresees a losing quarter and becomes stingy about providing information that could reveal the bad posture. All of these factors conduce to an optimistic biased behaviour.

#### 2.6.4.2 Overconfidence

Overconfidence in one's ability is a feature particularly salient among experts (DrKW Macro research, 2005). Notably, analysts' overconfidence is run by their privileged access to information that feed their illusion of knowledge. Although more information is not necessarily better information and can increase the forecast errors. The lack of feedback that is a key driver of this vicious behaviour doesn't play a paper in this case as professionals could track easily their errors and act accordingly. However, the same cognitive process at the origin of overconfidence prevents them to assess their former predictions and take note of their previous errors.

Huber, Huber, & Hueber (2019) examined forecasting patterns in the presence of information signals from different origins: professionals and non-professional players from two leading economies (the UK and USA). Overconfidence and miscalibration were found in both groups and it was strongly suggested that individuals were relying on others' forecasts to make their own predictions. This effect was more salient for neophytes who tend to rely on the signals provided by the experts than for the latest who are less dependent to these sources of information. As a matter of fact, individuals expect higher levels of forecasting errors among non-professionals whereas professionals do not show significant greater returns.

### 2.6.5 Biased forecasts or biased earnings?

Abarbanell & Lehavy (2002) studied the accuracy of the forecasted earnings per share (EPS). They defined the forecast errors as the EPS minus the "consensus earning forecasts

outstanding prior to announcement of quarterly earnings scaled by the stock price at the beginning of the quarter and multiplied by 100". The authors highlighted the presence of two types of asymmetry in the distribution of these forecast errors. These tail and middle asymmetries observed in the distribution help to explain why some divergent conclusions are reached regarding the direction of analysts' irrational behaviour. Then, they proved that accounting conservatism eases the writing of losses while the realisation of gains is more difficultly justifiable. Some of the consequences linked to this asymmetry are over interpretations of the underreaction to news observed in analysts' behaviour. With respect to the association between the accuracy of the earnings per share and the target prices, opposite results were found. Gleason et al. (2008) concluded on a positive correlation between both while Bradshaw, Brown & Huang (2013) don't support the association between these two forecast capabilities.

### 2.6.6 How are computed consensus target prices?

To estimate future price of a stock, analysts use different valuation methods requiring capabilities and activating the judgmental process. Demirakos, Strong & Walker (2010) discussed the impact on the accuracy of the target prices of two of the main valuation models. The single-period valuation (PE) model and the multiple period valuation (DCF) model are used by analysts in different types of growth environment and market conditions. Therefore, the choice of one model over the other is mainly motivated by different short-term factors e.g. 1-year returns and the DCF tends to be more solicited in period of uncertainty. However, no statistical difference was found between the accuracy of the two approaches. The estimates usually have a 1 year-horizon and are fundamental elements of the analyst' report because they depict analysts' sentiment about the companies. It appeared in the literature reviewed by Palley, Steffen & Zhang (2019) that most of the stock prices didn't reach the level predicted by the analysts and that a higher dispersion in the individual predictions implies less accuracy of the consensus forecasts regarding the actual prices. Consensus analysts' forecasts

reduce the bias induced by individual decision processes (Palley et al., 2019). Indeed, they represent the average of the predictions delivered by the analysts who are currently covering the firm. However, the degree of consensus represented by the standard deviation these average strictly conditions the results described above. A higher consensus (smaller standard deviation) involves better accuracy. The authors also pointed out another interesting feature regarding the deviation from the general agreement: when analysts are trying to enhance their reputation, their stock prices' forecasts tend to be closer from the consensus.

# Part III

# Empirical Analysis

## 3 Database

The second part of this work addresses empirically the accuracy of the forecasts delivered by the financial analysts that we discussed in the theoretical section. First, the database that we have constructed with the companies that are part of the Belgian and/or Dutch national indexes is presented. Next, descriptive statistics for the different variables and their interpretation are given as well as the results for the three measures of accuracy. Then, we set the research design where the methodology to compute these measures. After that, a transversal analysis of the results using linear regressions is conducted. Finally, we establish the link with the literature reviewed from a behavioural finance's view and conclude on our main findings.

### 3.1 Construction

The database gathers target prices from components of the Belgian (BEL20) and Dutch (AEX) national indexes. This choice was motivated by the membership of Belgium and the Netherlands to the BENELUX, a union of the two previously cited and Luxembourg. In term of demography and economy, these neighbouring countries are comparable. We decided to focus on these stocks for different characteristics related to the demand and offer of information. Indeed, stocks comprised in national indexes have a velocity of trading that involves higher level of liquidity and more symmetrical information distribution (Bonini et al., 2010). The consensus target prices and last prices were collected respectively monthly and daily on the period from 2010 to 2020. The financial analysis software Bloomberg provided us the data that we needed.

Concerning the evolution of the composition of the indexes, we monitored iShares AEX and Lyxor BEL20 two exchange-traded funds (ETFs) distributed by BlackRock and Lyxor, respectively an American and European asset management funds and ETFs providers. These two ETFs track the namesake indexes and were used as proxies to monitor the evolution of the composition of the two indexes distributed by Euronext. Indeed, ETFs offer to investors the opportunity to buy the more precise replication of a basket of different assets. Then, the basket is tradable as a single product whose price matches the portfolio tracked. External factors can slightly influence the price of the ETF and it may be possible that the fit is not perfect while the underlying securities should always be known and justified in function of the purpose of the ETF (Morningstar, 2020). In other words, the composition of the ETFs and the indexes they are tracking are equal.

Every quarter, the composition of the index is likely to change and the companies for which forecasts were provided on March 2010 are not necessarily part of the index as of today. The intention to focus on companies during their time in the index is due to the potential survivor bias that could arise from studying either only companies that have been part during the whole period or the newcomers that entered the index because of their recent successful financial results.

For example, Ontex (BB) was part of the BEL20 from March 2016 to March 2020 and the prices and target prices are exclusively collected from March 2016. Considering the forecast horizon of 12 months, we can draw the first conclusions on the accuracy of those predictions as of March 2017. We adapted the methodology from several authors (Bonini et al., 2010; Kerl, 2011) who are incorporated the target prices from the first day of the period under review when they studied stocks quoted in a national market.

Taking into consideration the minimum of 12 months to assess the accuracy of a forecast, only the companies that have been part of at least one of the indexes 13 months consecutively are reviewed.

By reviewing the forecasts provided for exiting companies as well (until they officially exit),

another part of the discrepancies between the forecasts and the prices observed is analysed. As we have previously seen, analysts tend to be unenthusiastic about the idea of delivering "bad" forecasts as it could cost them their privileged access to confidential information. Hence, keeping companies whose position in the index is compromised avoids denying the consequences of this bias.
Due to the length of the period considered, events affecting the structure of the equities occurred. These events are namely: buy-back, split or reverse splits and involve big changes overnight in the prices of the stocks.

For example, ArcelorMittal (NA) announced on $10^{th}$ May 2017 a reverse stock split of 3:1. Then, the price of the stock jumped from 7,54 to 22,26 Eur at the closing on $18^{th}$ May. Some authors (Bonini et al., 2010) chose to not include reports geared to companies experiencing this kind of redesign. However, others (Kerl, 2011) dealt with them as they are part of the daily corporate path of the firms examined. In this study, we decided to not exclude these companies and their target prices.

## 3.2 Indexes: AEX and BeL20

The BEL20 is the Belgian national index and is composed of maximum 20 companies listed on the Belgian stock exchange and considered as the most representative of the Belgian economy. It was launched on $18^{th}$ March 1991, 8 years after the first introduction of the AEX in January 1983. The capacity of the Dutch index is 25 companies picked according to the same criteria as for Belgium.
We chose to study the behaviour of firms that are included in these national indices since their benchmarking and the characteristics of the brokerage firms following them as well as their internal characteristics should be similar.
The rules of composition for both indexes are reviewed every year, but every quarter simplified

entry and exit is considered. These reviews are efficient after the Friday of the third week of March, June, September and December. The calendar coincides with the usual distribution of the events having an impact on the valuation of the shares of a company: the distribution of the dividends, the splits or any other major announcements.

The criteria of eligibility are based on two fundamental exigencies. First, the companies picked have the biggest free-float market capitalization of their local market. Second, the percentage of employees working in the country relative to the total number of employees of the consolidated group should represent at least 15%.

When free-float market capitalization is the approach of valuation selected to review an index, the weight given to each company is the current price of each share multiplied by the volume of shares that can be immediately traded in the market. This means that the "locked-in shares", detained by the government or other insiders (promoters, employees) are excluded. The motivation for electing free-float market capitalization over market capitalization is to guarantee the liquidity of the indexes and that investors can easily trade each individual asset.

The entry level for the BEL20 is fixed at the current level of the index at the review date multiplied by 300 000 € and companies that are already part of the index have to maintain a market float capitalization of at least 2/3 of the entry level (200 000 €).

The daily trading volume of each participant are individually aggregated yearly to fix the threshold and hold the standards of free-float velocity. The level is currently fixed at 35% for the newcomers and 25 % for the members.

As of March 2020, the full market capitalisation of the BEL20 equals 211,7 billion € while considering free float market capitalisation, the amount is almost cut by 40%, at 133,1 billion €. Concerning the AEX, the full market capitalisation stands at 657,6 Billion € and the free-float market capitalisation is 532,4 billion €.

The maximum weight given to a component at the yearly review, or capping is currently fixed by Euronext at 12% for the BEL20 and 15% for the AEX. However, since the free float market capitalisation of the constituents are constantly changing and the capping is

reset every March, values could excess this capping by a small percentage. For example, the current weight of ABinbev, a Belgian company, (as of April 30th 2020) is 13,67%.

## 3.3 Target Prices

The target prices covering the period from March 2011 to April 2020 were analysed. Analysts from several investment banks provide these forecasts for the largest capitalisation and more liquid stocks of the two markets considered. Kerl (2011) showed that analyses covering companies presenting these two characteristics were likely to be subject to more precise forecasts.

Belgium and the Netherlands have a similar Institutional and Governing framework. Bilinski et al. (2013) found evidence on the correlation between the quality of the regulatory environment and the accuracy of the price forecasts. The quality of this factor is determined in part by the degree to which investors are protected, the transparency of the financial environment and some cultural forces. The disclosure indexes measured by those authors are 0.695 for Belgium and 0.732 for the Netherlands. The coefficients attributed to these variables are substantially similar and by focusing on countries with the same level of institutional infrastructure, we control for possible external effects that could have arisen from comparing countries diametrically opposed.

The "Best Target Price" is the starting point of our analysis and is defined as the "12-month target price consensus, which excludes prices older than three months when it is calculated" (Bloomberg, 2020). Two notions must be highlighted and clarified in this definition. First, the *forecast horizon* for the individual target prices published in the reports are usually 12 months unless otherwise specified. Second, the target prices that we analyse in the present work are the *average of the individual target prices* emitted by professionals. Indeed, the data provider (Bloomberg) aggregates the available forecasts and computes their average.

The choice to focus on consensus target prices instead of analysing individual forecasts was

motivated by several elements. First, we have seen in the theoretical part that these consensus as they represent the mutual agreement exhibited smaller errors (Palley et al,. 2019). Second, it is very uncommon to observe a member of one of both indexes being followed monthly during the whole period by a same brokerage house.

In other words, brokers would deliver forecasts either on a irregular basis or less frequently than the monthly seting elected here. Thereby, an investor who would be dependent on these forecasts for making investment decisions is more likely to rely on the consensus forecasts than relying on a irregular release from a specific brokerage firm. Moreover, by representing the common agreement the consensus forecasts are less biased than individual forecasts for which the conflict of interests with the company analysed have not been determined.

According to Kerl (2011), these relations arise either from the bank having stakes in the company for which the report is issued or from the past or present role as an "underwriter" for shares of this firm. The results for the German market indicate that 43% of the sampling was subject to these conflicting relations.

As suggested by Bilinski et al. (2013), target price accuracy was evaluated in two stages. Three measures of the forecast accuracy are computed. The absolute target price error which is measured as a percentage of the price at the start of the period and two binary variables : one is achieved when the target price is reached at the end of the forecast horizon while the alternative one if the target price is met at least once during the period. Then, a comparison with naïve price forecasts computed by a random investor and based on the extrapolation of past performance is evaluated.

## 3.4 Target Prices' providers

HSBC, Societe Generale, Credit Suisse, Banco Santander or Exane BNP Paribas are some of the banks participating the most in the elaboration of the target prices that we analyse (Reuters, 2020). However, several "undisclosed" do also provide forecasts and are included in

the consensus under review.

As explained above, the consensus is an average of the current forecasts targeting the same horizon and there is no indication given on the dispersion of the data that are aggregated. For example, we reviewed the ranking of the analysts covering ING, a Dutch bank that is currently part both of the AEX and the BEL20 on the financial data provider Reuters Refinitiv. A ranking is established on the basis of the forecast accuracy over the 3 last fiscal years. The estimate accuracy ranges from 0 % for forecasts delivered by an analyst at KBC securities to 91% for the ones delivered by a professional at Keefe, Bruyette & Woods North America. The analysts at KBC securities covered 64% of the period while the most accurate covered 100%. These results that are transferable to the other companies show the disparity in the quality of the forecasts that compose the consensus target prices.

Moreover, these investment banks or brokerage firms could have several positions in the index. This means that there could be potential conflict of interests. The ownership analysis provided by Reuters, gives a hindsight on the top investors of our panel of companies.

The analysts can be engaged in three types of conflicting relationships: a pure relation of broker, a relation of underwriter and a local relationship if the analyst is established in the country of the firm analysed.

It seemed interesting to emphasize that for example BNP Paribas that provides numerous forecasts for the AEX is one of the top tier investors for the same index. The total value held by BNP Paribas in the index is 2,702 billion € (Reuters, 2020).

# 4 Statistics

## 4.1 Statistics of the companies covered

Over the period, 33 companies were part of the BEL20 for at least 13 months consecutively and 44 companies joined the AEX. 12 Belgian companies and 15 Dutch remained in their

respective group during the entire period, from 2010 to 2020. The period consists of maximum 110 months of consensus analysis per company. Through the analysis, the average time a company stays in its respective index is 67 months. Considering that we are working with consensus target prices and recommendations that imply averages, we back tested the results for the consensus recommendations when relying on quarterly data. This was done in order to control for the same data that might have been re-included in the means and that could have skewed our results. However, no significant difference between monthly and quarterly findings was outlined. Thus, we decided to keep on working with the monthly data which is more convenient since a few firms exit/enter the index before completing exactly a quarter. The core activities of these firms are divided into 11 sectors for the Belgian market and 14 for the Netherlands. The sectors of Industrial Goods & Services, Personal & Household Goods and Oil & Gas are not represented in the Belgian index. In the two markets, the top ten components weight for about 78 % of the index.

### 4.1.1 BEL20

As of April 2020, Banks and Health Care are the two sectors most allocated carrying 21,4 and 21,28 % respectively of the total weight. AB INBEV, only actor in the Food & Beverage and first individual component of the index lifts its sector that accounts for 13,67% of the portfolio. Far ahead from the smallest weight of the index assigned to Aperam (0,9%).
The average market capitalisation is 10,58 billion € and the median 6,92 billion €. These values lie between 1,61 and 68,53 billion €.
Three companies out of the 20 that compose the index are Dutch: ING Groep, Galapagos and Aperam. The two first are currently included in the AEX as well.

### 4.1.2 AEX

Technology is the sector most represented (22,24%), the holding ASML leader in its market weighting for 16,37% in the index. In second position comes the sector of Oil & Gas (14,6%),

entirely represented by Royal Dutch Shella (RDSA). Unilever (12,12 %) unique actor of Personal & Household Goods comes in third place.
In contrast, the smallest component (ABN Amro Bank) weights 0,55 %. The full market capitalisation of the components ranges from 3,25 billion to 103,2 billion € with an average of 25,99 billion € and a median of 11,98 billion €.

## 4.2 Descriptive statistics of the analysts' target prices

Overall, we processed 2026 target prices for the BEL20 and 2244 for the AEX. Controlling for the figures in common, we retain 4197 observations in the database dedicated to the two indexes combined. Due to the difficulty to find reliable data, Akzo Nobel (NA) and Unilever (NA) had to be removed from our analysis.

## 4.3 Statistics of the consensus

The consensus forecasts of the future stock prices are 77,63% of the time higher than the price at the issue date. Dutch forecasts are more optimist (83,11 %) than Belgian forecasts (72,31 %).
The consensus forecasts are on average 14,33% higher than the current price when they predict a positive evolution (3258 observations) and 7,43% below when they predict a negative evolution (939 observations). Altogether, the average implicit return as defined by Bonini et al. (2010) is 10,2 %.
In Belgium, consensus forecasts are on average 8,07 % higher than the stock price at the issue date. When the target price is above the current price (1407 observations), it is on average 13,15 % greater than the current stock price. When the target price is situated below the current price (522 observations), it is 6,69 % smaller than the current price.
For the Netherlands, the means are respectively 16,65% higher when the target price is above the current price (1865 observations) and 8,67% smaller when it is below (379 observations).

These average implied returns quantify the **optimism** as they represent the variation in percentage between projected and current prices.

At the international level, Bradshaw et al. (2013) document the optimism observed over the period from 1997 to 1999 comparatively to the period from 2000 to 2009. In the first period, the average implied returns were 32,9 % while in the second period this percentage drops to 24 %.

We see that our consensus forecasts are strongly less optimists than international evidence found by the previous authors. However, when we focus on national results, those are only slightly less optimists (Bilinski et al., 2013). Target prices geared to Belgian companies were on average 9.1% higher than the current price. This product jumped to 14.2 % in the Netherlands. Yet, their study was over the period 2002-2009 while ours targets the following decade (2010-2020).

We have seen in the section dedicated to target price providers that analysts who are employed by brokerage houses and investment banks can be involved in relationships of different nature with the companies that we investigate. In previous studies, and in the present one, it was not possible to isolate the effect on the trade-off of the forecast accuracy of both the positive and negative externalities arising from these relationships.

On the one hand, the error should decrease as a positive impact resulting from the privileged access to private sources of information. On the other hand, analysts engaged in those conflicts of interests tend to provide more optimist forecasts (Bradshaw et al., 2012) to maintain their privileged connections with the managers of the companies included in the BEL20 and AEX.

The high number of data provided in the present work and their consensual nature did not allow for a more in-depth investigation on the strength of the relationship between the companies of the two indexes and the forecasts' providers. However, the results of Bradshaw et al. (2013) gave an idea of the strongest forces at play between the companies and the

financial analysts.

## 4.4 Dispersion of analysts' recommendations

Analysts also deliver categorical recommendations alongside the predicted prices and EPS. These recommendations are divided into "sell", "hold" and "buy". They summarize the sentiment of the analyst regarding the future of the stock and offer to investors a straightforward material for their investments' decisions. In our sample, we collect the equivalent of 3880 months of investment recommendations on the same database analysed for the descriptive statistics in the previous subsection. We find that "buy" are the most distributed (46,89%), followed by "hold" (40,52%) and "sell" (12,59%). Our findings are similar to Kerl (2011) on the German market where the distribution of recommendations' levels is respectively 45,5 %, 42,2 % and 12,3%.

We also review an additional variable that aggregates the number of analysts being recorded in the monthly consensus. ABinBev (BE) and ArcelorMittal (NA) are the most followed companies of their market with an average of respectively 35 and 36 analysts being recorded in the monthly consensus forecasts. A company for which the number of analysts making forecasts is high is more likely subject to high-quality forecasts. This positive externality should brought by the competition amongst analysts.

In addition, the general feeling of the analysts currently covering the firm is also included and measured on a continuous scale from one to five, five being the most optimist. These results from the aggregation of individual ratings are "strong sell" equals to 1, "sell" equals to 2, "hold" equals to 3, "buy" equals to 4 and "strong buy" equals to 5.

Through the entire period, we find an average consensus recommendation of 3,69. These values range between 2,25 for Colruyt (BB) and 4,91 for ARGX (BB).

# 5 Accuracy of the target prices

## 5.1 Accuracy of the consensus' target prices

Overall, 37,19 % of the time (1561 observations) the target price is reached at the end of the forecast horizon. We consider that a target is reached when the stock price is greater or equal to the target price delivered 12 months before. This represents 36,67 % of the Dutch observations (823 target prices) and 38,04% of the Belgian ones (770 observations). Nonetheless, we could relax the conditions of success for this binary variable. In that case, a stock price greater than the target price at any time during the 12-months horizon involves an encountered target. Indeed, when an analyst makes a forecast it is hardly possible for him to plan exactly the date at which the target price will be met. Under these assumptions, 62,08 % (2606 observations) of the target prices are met at least once during the period. The distribution of this result is 61,76 % in the Netherlands (1386 cases) and 68,31% in Belgium (1384 cases). The outcomes of our study are slightly better than the results highlighted in Germany by Kerl (2011). He concluded that 56,53 % of the target prices had been achieved in the 12 months following the release of the reports.

## 5.2 Accuracy of the target prices per year

The accuracy of the target prices for the two indexes reunited as well as each index individually has been computed year by year from March 2011 to April 2020. Thus, the first interval analysed (2011) includes 10 months and the last one (2020) 4 months. The number of observations for each year is also reported and there are small variations in the number of observations reported from year to year. This is due to the few companies that had to be removed and the number of components in the indexes that is not always equal to its maximum capacity.

| Year | n | Error | AEX | BEL20 |
|---|---|---|---|---|
| 2011 | 417 | 0,2631 | 0,2754 | 0,2418 |
| 2012 | 492 | 0,3413 | 0,3717 | 0,3055 |
| 2013 | 487 | 0,2604 | 0,3047 | 0,2065 |
| 2014 | 453 | 0,1790 | 0,2019 | 0,1545 |
| 2015 | 456 | 0,2192 | 0,2500 | 0,1875 |
| 2016 | 435 | 0,1938 | 0,2268 | 0,1576 |
| 2017 | 443 | 0,1896 | 0,2005 | 0,1762 |
| 2018 | 446 | 0,2254 | 0,1873 | 0,2634 |
| 2019 | 424 | 0,2748 | 0,2730 | 0,2831 |
| 2020 | 145 | 0,2997 | 0,3743 | 0,2623 |
| Total | 4198 | 0,2416 | 0,2603 | 0,2235 |

We observe substantial variation, average forecast error varying by up to 100 % across the years. In 2012, the average forecast error was 34,13 % of the last price registered at the issue date. Two years later in 2014 this same ratio had dropped to 17,9%. Throughout the entire period, the average forecast error is 24,16 % .

The BEL20, with an average error of 22,35% over the entire period exhibits a persistent better accuracy than the AEX (26,03 % ). Except in 2018 and 2019, the predictions for the BEL20 family were every year more accurate than for the AEX. The greatest discrepancy between the respective yearly forecast quality occurred in 2013. That year, the forecast error had an average of 30,47% in the Dutch index and 20,39 % in the Belgian index.

## 5.3 Comparison with naïve forecasts

The naïve forecasts for the period March 2012 to April 2020 (3419 forecasts) were computed as described in the Research Design. The returns of a one-year buy-and-hold policy were needed for each stock. Thus, our descriptive analysis starts two years after the first stock

prices at our disposal. We find over this period an average absolute error of 30,67 % of the initial stock price whereas the absolute target price error is 23,07 %. In other words, the predictions of professionals are on average 7,6% more accurate than simple extrapolations computed by non-professional investors. These results are consistent with Bonini et al. (2010) who found a different accuracy between the two groups of 9.8 %. Hence, reports released by analysts provide useful information to investors since by referring to these figures their investment decisions will be on average more accurate.

# 6 Research design

We worked with three measures to establish the forecast accuracy. Those two indicator variables and one continuous variables were inspired by Kerl (2011) and Bilinski et al. (2013). The second binary variable was introduced in order to fill the exclusion of the possibility to study the impact of this accuracy on short-term sellers who could emit automatic orders once the target price is reached. By considering both the prices at the end of the forecast horizon and within the horizon, we take into account the diversity of the strategies adopted by market participants regarding their portfolio management.

## 6.1 Target price met at the end of the forecast horizon

The binary variable informs on whether the prediction is effectively attained at the end of the forecast horizon. The treatment of the data differs regarding the direction of the inequality between the target price and the stock price at the issue date.

When $TP > P_s$ : TPmetEnd = 1 if $P_e \geq TP$; TPmetEnd = 0 otherwise

When $TP < P_s$ : TPmetEnd = 1 if $P_e \leq TP$; TPmetEnd = 0 otherwise

Where: TP = Target price at time t for a 12-month horizon

$P_s$: Current stock price at the issue date

$P_e$: Stock price at the end of the forecast horizon

## 6.2 Target price met at any time during the forecast period

This indicator is justified by the more informative power of an inaccurate forecast that would have been reached during the period over an equally inaccurate forecast that would not have been reached at any time during the interval. This measure equals 1 if the target price is met at any time during the period of 12 months following the release of the forecast. Observations are classified regarding the curse of the forecast compared to the current price. We gather the maximum and minimum prices for each company and horizon. When the ratio is greater than one, we evaluate the position of the maximum price registered during the period regarding the target price. When the ratio is smaller than the unit, the minimum price is considered. The indicator is constructed as follow:

When $TP > P_s$ : TPmetWithin = 1 if $P_{Max} \geq TP$; TPmetAny = 0 otherwise

When $TP \leq P_s$: TPmetWithin =1 if $P_{min} \leq TP$; TPmetAny = 0 otherwise

Where

$P_{Max}$: Maximum price reached by the stock during the 12-month period

$P_{min}$: Minimum price reached by the stock during the 12-month period

## 6.3 Target Price Error

The two indicators previously described do not provide any evidence on the magnitude of the discrepancy. Target prices that would have been missed by a small percentage are equally rejected as the ones missed by a greater percentage. We measure the unsigned error to avoid that errors with opposite signs cancel each other. This would lead to a positively biased accuracy. Moreover, we compute as a continuous variable the absolute error of the forecast as a percentage of the price at the issue date (Bilinski et al., 2013) to avoid issues of non-stationarity. This feature also makes possible the comparison of errors between stocks of different companies with heterogeneous initial prices .

The forecast accuracy is measured by the Target Price Error (TPE) as follow:

$$TPE = \frac{|TP - StockPrice_f|}{StockPrice_i}$$

Where:

$StockPrice_i$ is the last price of the stock at the date the report is published.

$StockPrice_f$ is the stock price at the end of the 12-month forecast period.

### 6.4 Naïve forecasts

Naïve forecasts also called Bayesian forecasts are computed by extrapolating the returns induced by a passive investment policy over the 12 months prior to the forecast. Thus, the forecasted price is equal to the raw returns times the price at the issue date. The absolute error of this very simple type of forecast is computed exactly as with target prices. For that,

$$\text{Forecast} = (BHR + 1) * P_s$$

Where:

$BHR$ = return calculated as a percentage of the stock price at the fictive buy date.

## 7 Transversal analysis of the results

### 7.1 Role of market momentum

To measure the hypothetical relation between the amplitude of the forecast error and the expansion of the market (respectively Dutch and Belgian), we used as a proxy the market momentum of the two respective economies. Bonini et al.(2010) defined the market momentum as the "variable given by the raw returns of the market index in the six months before the report's issuance date".

We referred to the exchange traded funds (ETFs) iShares AEX and Lyxor BEL20 to monitor the market raw returns over the 6 months preceding the forecasts of the two namesake indexes. These two ETFs replicate the composition of the indexes. Hence, the part attributed to each component is very close to their respective weighting in the index. However, the price of the product is not equal to the current value of the index. For example, as of April 30rd, BEL20 closing value was 3099,1 € whereas the corresponding value of the ETFs was 45,995 € . The returns of the index and the ones of its tracking ETFs are correlated, and are almost entirely explained by the variation in the prices of the underlying securities of the index. Thus, the use of the corresponding ETF for each market is relevant in our study to establish the returns of the markets of reference.

For each company comprised in those two indexes, the link between the target price error and the market returns was established. For that, we ran 62 individual linear regressions linking the continuous error that we have computed in the previous section and the raw returns of the two ETFs.

For all the linear regressions, the $R^2$ adjusted that measure the quantity of variation explained by the model range between less than 1% and 10 %. This means that a very small part of the error observed is a straightforward result of the market returns in the 6 months previous to the predictions.

For the AEX, the variables are significantly (at p-value = 10%) and negatively correlated for one out of two companies. These results support the literature (Bonini et al., 2010) showing an inverse relationship between the recent changes in the performance of the market and the accuracy of the predictions. However, in the other half of the cases, the results either don't show a regular pattern or are insignificant at the threshold set. Thus, these results were not taken into consideration.

Regarding the BEL20 and under the same conditions as for the AEX, no homogeneity in the coefficients was found. Therefore, we cannot conclude quantitatively on the direction nor on the strength of the relation between the market momentum and the magnitude of the error.

## 7.2 Role of past target price accuracy

We discuss the persistent ability of analysts covering some companies to maintain their previous level of accuracy. Authors (Bonini et al., 2010) showed that past target price accuracy was in part explaining current accuracy. We complement their results by studying whether there exists a pattern in the continuity of target price accuracy (represented by TPError) for a one, two and three-years' horizon. We chose to consider results for these three horizons since on average analysts are following companies for 2,705 and 2,927 years in Belgium and the Netherlands respectively (Bonini et al., 2010).

Only companies for which predictions are available for the 14 months following the error regressed are included in the analysis. Indeed, a regression on past error 12 months before was done and we needed at least two observations (since we have two variables to estimate: the intercept and the slope). That is to say, for regressions at T-1, target prices for at least 26 months should be available and for regressions at T-2, we should be able to gather observations for 38 months on the same basis. This condition reduces considerably the number of companies that we investigate for the persistence in the accuracy. Moreover, for several companies only regressions at T-1 and/or T-2 were done. The detail of the coefficients and adjusted $R^2$ are in the annexes. For the Belgian index, we regressed for 25 of the members with a one-year lag, 22 with a two-years lag and 18 with a three-years lag. Out of these individual regressions, respectively 8, 6 and 7 were significant at the level $\alpha = 5\%$. For the Dutch index, the results of 28 companies were regressed with a one-year lag, 25 with a two-years' lag and 21 with a three-years' lag. Respectively 16, 9 and 4 of them were significant at the 5% level. In our analysis, we take into consideration only the significant results for obvious reasons of consistency of the conclusions. At T-1, most of the regression coefficients (68,75% for the AEX) are smaller than one and negative. The negative sign of the coefficient suggests that as the past error increases, the present error tends to decrease whereas the value depicts the strength of the dependency between lagged and present accuracy. For the

BEL20 the results are more mitigated with half of the coefficients being negative and the other half being positive. The regression coefficients range from -0,886 to 1,42 for the Dutch index and between -0,865 and 1,676 for the Belgian index. For T-2 and T-3, less homogeneity in the coefficients is observed and the persistence in the quality of the predictions cannot be ascertained. Our findings contradict Bonini et al. (2010) where the correlation between past and present predictions' quality was positive.

## 7.3 Role of the quality of firm's environment

The number of analysts dedicating their skills and time to follow a company is used as a proxy for the competition amongst analysts. When the presence of analysts covering a firm is increased, the quality of the forecasts should evolve in the same direction. As a matter of fact, their predictions are more easily compared to the ones of their fellow from rival brokerage firms or investment banks. This gives them incentives for delivering forecasts of better quality. Moreover, in the present study we would like to emphasize that the target prices that are processed are those of the consensus. Thus, gaining insight on the dispersion of the predictions helps us to better understand what was the individual sentiment of the analysts on the future prices when the reports were released.

We verify whether there exists a relationship between the average number of analysts following a firm and the forecast accuracy of the latest. We expect a negative coefficient between the target price error and the number of analysts. However, our results did not allow us to statistically identify a relationship between the variables since the coefficients were not significant. For each observation of both variables, we have been working with means without taking into consideration the number of observations aggregated in those. Thus, it seems that these results could be biased.

For example, only 2 months of projected prices by the 12 analysts for IMCD (NA) were reflected in the means solicited for the regression since the company joined the AEX in March

2019. The analysts performed well above average over this short period with an average forecast error of 11,25 %. On the other side, 110 months of predictions computed by the 35 analysts (on average) following ABinbev (BE) were needed to regress the observations. In that case, the average forecast error is 21,03%.

Here, the same weight is given to a performance on a very short period and to the fruit of nine years of predictions. Observations issued from newcomers or companies that could have leave prematurely the indexes and performed well, like IMCD (NA) can skew the results towards the outliers that represent a tiny proportion of our sample.

The 25 "fossils" or companies that are registered in the indexes since the first day of our analysis are the most followed of the sample. Indeed, for 19 out those 25 companies, the average number of analysts covering the firm is above the median (21,8 analysts) of the 58 companies included in this part of the analysis.

This is not surprising since the criteria of composition of the two indexes are based on the free-float market capitalisation and on the liquidity of the stocks. Because analysts tend to release reports for companies with these features (Bonini et al., 2010), it is coherent that we observe a higher concentration of analysts around these companies.

Moshirian, Ng & Wu (2009) exposed the negative relation between the size of the company and the forecast error. In larger companies, the quality of the information was presented as superior and the resulting forecast error as inferior. We were not able to confirm those results.

## 7.4 Comment on the validity of our results

For the transversal analysis of our results, we ran simple linear regressions for each one of the companies to control for a relation between the forecast accuracy and different independent variables. For establishing the role of the momentum or the role of past accuracy in present accuracy, we needed more observations (at least 14 months of target prices per company)

due to the requirements of the simple linear regression. Those stipulate that this is necessary to use at least 2 observations to run it and we needed to get rid of some companies for this reason.

Even if we are analysing indexes' members, we decided to not aggregate the prices and predictions to not lose track of the individual variations and conclusions. Hence, we obtained individual results and we cannot (most of the time) draw a single conclusion for the full indexes even if we perceived general trends. These trends are translated formally in the descriptive statistics and in the different measures of the accuracy. In the next section, we put in perspective these results from a behavioural finance's view.

# 8 Behavioural finance's view

In this section, we will first analyse the key findings regarding the companies of the AEX and the BEL20 during the period 2010-2019 in relation with two of the principal biases that we highlighted in the literature review. We found that analysts were particularly subject to over-optimism and overconfidence and investigate if these traits are exhibited in our results.

## 8.1 Analysis of the results from a behavioural perspective

### 8.1.1 Over-optimism

Our results suggest that analysts distribute more easily flattering recommendations and that when the future of an enterprise is foggy, they are more reluctant to provide negative forecasts. Indeed, almost half (46,89%) of the investment recommendations incite the investor to buy the stock while 12,59 % advise for a selling of the stock. The remaining 40,52% of the recommendations are neutral (hold). Moreover, in more than three out of four times (77%), the target price is above the current stock price. The average yearly implied return is 10,2 %. Our findings support precedent literature (Lim, 2001) that justified the optimism

bias by the incentive that those analysts could have to maintain warm relationships with the client-companies. Brown, Call, Clement & Sharp (2015) conducted a research on 365 sell-side analysts to better understand their motivations and the inputs they valued the most to produce recommendations and forecasts. They outline the strong motivation to meet their investing clients' expectations. Indeed, the private information that analysts can access by maintaining a private relation is considered as essential for the making of their predictions. The majority of the analysts surveyed report that they had at least 5 annual private contacts with some of the highest members of the board (CFO or CEO) and almost all the analysts (98,4%) had at least one contact per year with the same executives. Moreover, analysts added that the information coming from these sources was more valuable than the data they collect directly on the field as they make them standing apart. During these private conversations, analysts have the opportunity to get partial feedback on the hypothesis of the models they use for redacting the key predictions in their reports. However, we can doubt on the total objectivity of the feedbacks given by the executives of the concerned company. The management do also reach out to the analysts in order to help them with the interpretation of recent corporate events such as earnings announcements.

The authors analysed the way the management arranges the order of their contact with the analysts to push upwards the consensus predictions -that we are analysing in the present study. By starting the discussion with the analyst having provided the less flattering recommendation and highlighting that every other analyst has higher forecasts and carrying on with the second less flattering etc, a manager will induce the forecasts to go up. This technic relies on the tendency of the analysts to stay close from the consensus.

As discussed in the theoretical part, the herding behaviour is also salient among experts and could bring some answers in the study of the optimistic bias. Indeed, the financial analysts interrogated by Brown et al. (2015) have admitted reviewing their fellow's reports before publishing their own report to check for prominent discrepancies and to find their reason. Those experts know the reliability of their colleagues from competing firms and tend to drive

their results towards the ones of the most renowned analysts.

These puzzling relations and conflict of interests help us to better understand the forces at stake and the reason of the optimistic results that we have encountered. The presence of a bias cannot be denied in the sense that the predictions are most of the time upward biased. Even though, taking into consideration the value that analysts grant to their relationship with the managers in order to deliver forecasts with smaller variance, this bias cannot be considered as irrational (Rogers & Grant, 1997).

### 8.1.2 Overconfidence

Different drivers are at the origin of overconfident behaviours. The privileged access to some sources of elusive information discussed in the previous section is one of the inhibitors for this type of behaviour.

Another key driver of this somehow vicious attitude is the lack of feedback. In such situation, the expert could not keep a track of whether his predictions and/or recommendations have been correctly realised. Theoretically, financial analysts can verify very easily the convergence of their predictions with the effective prices as the latter are updated instantly by all the financial data providers.

Practically, we noticed that the analysts releasing reports for Belgium and the Netherlands were on average following the firms for respectively 2.7 and 2.9 years. The target prices and investment recommendations have a horizon of 12 months. Thus, analysts can difficulty review and react accordingly to their predictions' process before the end of this period. By this I mean that, even if the feedbacks are easily available, the analysts may not follow the companies for a period sufficient for drawing the most accurate conclusions on their working approach.

Over-optimism and overconfidence are two distinct biases. However, it is very likely that the presence of one induces the other. Previous studies have shown the strong relation between both. This is not surprising since we find some of the same key drivers for these deviant

behaviours (Fabre & Heude, 2009).

# 9 Conclusion

In this empirical research, we attempted to determine the accuracy of consensus target prices for firms included in two European indexes. To do so, we have first studied the composition of the BEL20 and its Dutch counterpart, the AEX, over the period 2010 to 2020. These target prices are an integral part of financial analysts' reports and are generally delivered along with recommendations and earnings forecasts. We have also combed through the buy/hold/sell investment recommendations in order to verify the results issued by previous authors (Bonini et al., 2010; Kerl, 2011; Bradshaw et al., 2013) regarding analysts' behaviour.

In order to produce statistically consistent results, we have descriptively deconstructed our database of more than 4000 consensus target prices and 4000 recommendations. The statistics concerning the distribution of the recommendations, the location of the target prices compared to the current prices and the implied returns have shown us results quite similar to the work carried out in different markets such as the USA, Italy, Germany or Europe in general (Bonini et al., 2010). The studies we compared our results with were mostly conducted over the period from 2002 to 2010 and therefore prior to the period of our observations (2010-2020).

We tested the accuracy of the predictions in three different ways to assess their quality and the magnitude of the errors. The results showed that the error rate averaged 24.16% of the initial price and that only 37.19% of the time the target prices were reached at the end of the period. This success rate, which we can qualify as very moderate, is partly due to experts' cognitive biases, who tend to make rather flattering predictions. We also controlled for the potential role of past accuracy and the market momentum in explaining present accuracy. The consensual nature of the predictions as well as the non-aggregation of the

different prices more than certainly played a role in the impossibility of establishing formal statistical relationships between these variables. We focused on consensus predictions and were unable to determine the name of each brokerage firm being retained in the average of the predictions. A firm that is followed by a small number of analysts has the same weight in our conclusions as a larger firm that is more closely followed. Moreover, it would have been interesting to carry out this study differently by calculating the consensus ourselves in order to be able to study more deeply the accuracy of analysts working at specific brokerage firms/investment banks. This approach would have probably enable the setting of multiple linear regressions by means of which we could have arrived to additional conclusions.

Target prices are issued by analysts employed by internationally renowned brokerage firms as well as smaller entities whose origin remained undisclosed. The remuneration scheme of these professionals is not entirely transparent and there are many conflicts of interest between the firms for which the predictions are made and the brokerage houses. Indeed, the accuracy of financial analysts' forecasts as we measured it is far from being the first element determining analysts' remuneration. Moreover, analysts are pushed to make optimistic predictions in order to keep in close contact with the management of the companies they follow.

These different factors as well as human nature imply the presence of behavioural biases. In the empirical part, we decided to focus on two of the most documented biases in the literature and the most quantifiable among financial analysts: over-optimism and over-confidence. As we expected, and in view of the results obtained, the presence of these biases has been confirmed.

While the presence of these biases is undisputed, the irrationality of the experts making these predictions cannot be asserted. Indeed, their over-optimism and over-confidence is not hazardous. These analysts derive an informational advantage from this non-linear rationality,

which is an indirect way of continuing to provide predictions that take into account all the information deemed relevant.

# Part IV

# General conclusion

This research aimed to address the problematic "How predictive are analyst's forecasts? A behavioural finance's view". Based on a quantitative and qualitative analysis of target prices for the stocks comprised in the BEL20 and the AEX, it can be concluded that these predictions lack accuracy. The results indicate that predictions are upward biased as a result of the over optimism and overconfidence that financial analysts display.

The present study tackles the accuracy of the consensus target prices from a behavioural finance's view. However, we started the research without prejudice on whether the forecasts were biased. To do so, we made possible the understanding of classical theories, relying on the efficient market hypothesis e.g. the Random Walk and the CAPM, as well as the elements discrediting them. Empirical evidences weakening the assumption of an efficient market were presented to the reader. The momentum effect, the size and January effects or the existence of arbitrage opportunities proved that the markets rarely behave consistently.

We linked classical with behavioural theories. For that, we proved to which extent modern theories intended to answer to anomalies that classical theories could not address. Then, we reviewed several research in the field of behavioural finance in order to better identify the biases that analysts face. These experts are subject to judgmental errors that are classified into three categories: Heuristics simplifications, emotional biases and market anomalies. We decided to focus on two features well documented in the literature related to forecasts and analysts: overconfidence and over-optimism.

We pointed out that key elements of analysts' reports, demonstrate an excess of optimism

and confidence. The first behavioural bias is translated into mathematical language by target prices being 77,63 % of the time higher than the current prices and buy recommendations representing 47 % of the panel, whereas only 13 % of the recommendations advise a selling of the stock. Regarding overconfidence, we found an average error rate of 24,16 % through the period 2010-2020. Moreover, only 37 % of the target prices were reached by the end of the forecast horizon.

We attempted with very limited success to control the impact of past accuracy, the market momentum and the quality of firm's environment on target price accuracy. As a reminder, we did not aggregate the individual data and we obtained coefficients for each individual stock. Thus, we were unable to draw general conclusions about the role of these different factors on present accuracy. Moreover, we decided to work with consensus target prices, to take the perspective of investors who may not want to rely on the target prices released by a specific brokerage firm/investment bank. However, the consensual nature of those predictions implied limitations. Indeed, we could not determine the dispersion of the individual forecasts comprised in these averages. It might be interesting for future studies to use non-consensual target prices to control whether the deviation from the consensus has relevant consequences.

# Part V

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Part VI

# Appendix

## A Components of the AEX and the BEL20

**Components AEX**

| Name | Ticker | Entrance | Exit |
|---|---|---|---|
| ABN Amro Bank | ABN NA | March 2016 | |
| Adyen | ADYEN NA | March 2019 | |
| Aegon | AGN NA | March 2010 | |
| Ahold Dehlaize | AD NA | March 2010 | |
| ArcelorMittal | MT NA | March 2010 | |
| ASR International | ASM NA | March 2018 | |
| ASML Holding | ASML NA | March 2010 | |
| Boskalis- Westminster | BOKA NA | March 2010 | March 2018 |
| DSM | DSM NA | March 2010 | |
| Galapagos | GLPG NA | June 2016 | |
| Heineken | HEIA NA | March 2010 | |
| IMCD | IMCD NA | March 2019 | |
| ING Groep | INGA NA | March 2010 | |
| Takeaway | TKWY NA | March 2020 | |
| KPN | KPN NA | March 2010 | |
| NN Group | NN NA | March 2015 | |
| Philips | PHIA NA | March 2010 | |
| Prosus | PRX NA | December 2019 | |
| Randstad | RAND NA | March 2010 | |
| RELX | REN NA | March 2010 | |
| Royal Dutch Shella | RDSA NA | March 2010 | |
| Unilever | URW NA | March 2010 | |
| Unibail-Rodamco-Se | UNA NA | March 2010 | |
| Wolters Kluwer | WKL NA | March 2010 | |
| Aalberts | AALB NA | March 2015 | March 2020 |
| Air France-KLM | AF FP | March 2010 | March 2014 |
| Akzo Nobel | AKZA NA | March 2010 | March 2016 |
| Altice | ATC NA | March 2015 | March 2019 |
| Aperam | APAM NA | March 2011 | March 2014 |
| Bam Groep | BAMNB NA | March 2010 | March 2011 |
| Corio | CORI NA | March 2010 | March 2015 |
| Delta Lloyd | DL NA | March 2014 | March 2016 |
| Douwe Egberts | DE NA | March 2013 | March 2014 |
| Fugro | FUR NA | March 2010 | March 2015 |
| Gemalto | GTO NA | March 2014 | March 2019 |
| IMCO | IMCO NA | March 2013 | March 2014 |
| OCI NV | OCI NA | March 2014 | March 2016 |
| PostNl | PNL NA | March 2010 | March 2014 |
| SBM Offshore | SBMO NA | March 2010 | March 2015 |
| TNT | TNTE NA | September 2011 | March 2016 |
| Tomtom | TOM2 NA | March 2010 | March 2013 |
| Vopak | VPK NA | March 2015 | March 2019 |
| Wereldhave | WHA NA | March 2010 | September 2011 |
| Ziggo | ZIGGO NA | March 2014 | March 2015 |

**Components BEL 20**

| Name | Ticker | Entrance | Exit |
|---|---|---|---|
| Ackermans & van Haaren | ACKB BB | March 2010 | |
| Ageas | AGS BB | March 2010 | |
| AB Inbev | ABI BB | March 2010 | |
| Aperam | APAM NA | March 2017 | |
| arGENx | ARGX BB | June 2018 | |
| Barco | BAR BB | March 2019 | |
| Cofinimmo | COFB BB | March 2010 | |
| Colruyt | COLR BB | March 2010 | |
| Galapagos | GLPG BB | March 2016 | |
| GBL | GBLB BB | March 2010 | |
| ING Group | INGA NA | March 2016 | |
| KBC | KBC BB | March 2010 | |
| Proximus | PROX BB | March 2010 | |
| Sofina | SOF BB | March 2017 | |
| Solvay | SOLB BB | March 2010 | |
| Telenet Group | TNET BB | March 2010 | |
| UCB | UCB BB | March 2010 | |
| Umicore | UMI BB | March 2010 | |
| WDP | WDP BB | March 2019 | |
| Befimmo- Sicafi | BEFB BB | March 2010 | March 2016 |
| Bekaert | BEKB BB | March 2010 | March 2018 |
| Bpost | BPOST BB | March 2014 | March 2019 |
| Delhaize Group | DELB BB | March 2010 | March 2017 |
| Delta Lloyd | DL BB | March 2013 | March 2016 |
| Dexia | DEXB BB | March 2010 | March 2012 |
| D'Ieteren | DIE BB | March 2012 | March 2016 |
| Elia | ELI BB | March 2012 | March 2016 |
| Engie | GSZB BB | March 2010 | March 2019 |
| Mobistar | OBEL BB | March 2010 | March 2013 |
| Nyrstar | NYR BB | June 2011 | March 2013 |
| Omega Pharma | OME BB | March 2010 | December 2011 |
| Ontex Group | ONTEX BB | March 2016 | March 2020 |
| Thrombo Genics | THR BB | March 2013 | March 2014 |

# B Regression coefficients, $R^2$ and p-value for the persistence in the forecast accuracy

| | T-1 | | | T-2 | | | T-3 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coeff | p-value | R^2 | Coeff | p-value | R^2 | Coeff | p-value | R^2 |
| reg1 | 1,4200 | 0,0014 | 0,2857 | 0,1980 | 0,7370 | -0,0548 | 1,6100 | 0,5300 | -0,1100 |
| reg2 | -0,1954 | 0,0379 | 0,0034 | -0,1750 | 0,0531 | | -0,1900 | 0,0478 | 0,0396 |
| reg3 | -0,4138 | 0,0000 | 0,1565 | 0,3577 | 0,0010 | 0,1110 | -0,3658 | 0,0015 | 0,1191 |
| reg4 | -0,0993 | 0,3740 | -0,0021 | -0,5146 | 0,0000 | 0,2018 | 0,1035 | 0,4370 | -0,0054 |
| reg5 | -0,2983 | 0,0032 | 0,0776 | | | | | | |
| reg6 | -0,4345 | 0,0001 | 0,1897 | 0,0936 | 0,3800 | -0,0036 | -0,1516 | 0,1680 | 0,0197 |
| reg7 | 0,0127 | 0,8990 | -0,0103 | -0,0642 | 0,5110 | -0,0067 | 0,0691 | 0,5270 | -0,0082 |
| reg8 | -0,8100 | 0,1890 | 0,0380 | 0,2935 | 0,6600 | -0,0860 | | | |
| reg9 | -0,0296 | 0,7760 | -0,0096 | 0,1080 | 0,2700 | 0,0028 | 0,1010 | 0,3200 | 0,0316 |
| reg10 | 0,0068 | 0,5370 | -0,0064 | -0,1400 | 0,1800 | 0,0096 | -0,3100 | 0,0046 | 0,0950 |
| reg11 | 0,2780 | 0,0077 | 0,0620 | -0,1150 | 0,2280 | 0,0056 | -0,0048 | 0,9400 | -0,0138 |
| reg12 | -0,8540 | 0,0228 | 0,1118 | 0,5550 | 0,3710 | -0,0068 | 0,6210 | 0,4683 | -0,0350 |
| reg13 | 0,2354 | 0,0007 | 0,1030 | 0,1331 | 0,0099 | 0,0656 | 0,0425 | 0,3020 | 0,0011 |
| reg14 | -0,1307 | 0,1740 | 0,0089 | 0,2550 | 0,0020 | 0,0973 | 0,0014 | 0,8390 | -0,0133 |
| reg15 | 0,5896 | 0,0000 | 0,3225 | 0,1641 | 0,1830 | 0,0093 | -0,4696 | 0,0002 | 0,1700 |
| reg16 | -0,2780 | 0,0207 | 0,0446 | -0,2790 | 0,0289 | 0,0444 | 0,0783 | 0,5850 | -0,0097 |
| reg17 | 0,2733 | 0,0035 | 0,0758 | 0,1670 | 0,1040 | 0,0196 | -0,0445 | 0,7610 | -0,0123 |
| reg18 | -0,2679 | 0,0079 | 0,0615 | -0,2716 | 0,0081 | 0,0696 | -0,0868 | 0,4570 | -0,0061 |
| reg19 | -0,3020 | 0,0034 | 0,0770 | -0,0288 | 0,7880 | -0,0112 | -0,1203 | 0,3070 | 0,0008 |
| reg20 | -0,5360 | 0,0029 | 0,3350 | 0,6195 | 0,0017 | 0,6930 | | | |
| reg21 | 0,0496 | 0,0260 | 0,3184 | | | | | | |
| reg22 | -0,1110 | 0,7411 | -0,0253 | -0,5439 | 0,1750 | 0,0384 | 1,1509 | 0,1520 | 0,1023 |
| reg23 | 0,1499 | 0,6013 | -0,0309 | -1,2990 | 0,0020 | 0,5601 | | | |
| reg24 | -0,6421 | 0,0000 | 0,4118 | 0,3677 | 0,0083 | 0,2339 | -0,0107 | 0,9771 | -0,0908 |
| reg25 | -0,8860 | 0,0105 | 0,4137 | | | | | | |
| reg26 | -0,1574 | 0,3930 | -0,0089 | -0,4994 | 0,0597 | 0,1457 | 0,3772 | 0,2195 | 0,1390 |
| reg27 | 0,2857 | 0,1727 | 0,0254 | 0,3007 | 0,4520 | -0,0176 | 0,4335 | 0,1150 | 0,1386 |
| reg29 | -0,1205 | 0,5800 | -0,0299 | -0,6513 | 0,0001 | 0,7991 | | | |
| | | | | | | | | | |
| MIN | -0,886 | | | -1,299 | | | -0,46956 | | |
| MAX | 1,4200 | | | 0,6195 | | | 1,6100 | | |

| | T-1 | | | T-2 | | | T-3 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coeff | p-value | r^2 | Coeff | p-value | r^2 | Coeff | p-value | r^2 |
| reg1 | -0,0423 | 0,6780 | -0,0086 | -0,1617 | 0,1300 | 0,0155 | -0,2020 | 0,0680 | 0,0323 |
| reg2 | 0,3419 | 0,0000 | 0,2678 | 0,2582 | 0,0000 | 0,2931 | -0,0004 | 0,9910 | -0,0139 |
| reg3 | -0,1950 | 0,0589 | 0,0266 | 0,0506 | 0,6710 | -0,0097 | 0,1528 | 0,9000 | -0,0137 |
| reg4 | -0,4236 | 0,1030 | 0,1404 | | | | | | |
| reg5 | -0,1944 | 0,1300 | 0,0136 | | | | | | |
| reg6 | -0,4596 | 0,0000 | 0,1920 | -0,2100 | 0,1420 | 0,0139 | 0,8648 | 0,0000 | 0,3441 |
| reg7 | -0,8648 | 0,0740 | 0,0906 | -0,6629 | 0,3474 | -0,0034 | | | |
| reg8 | 0,0787 | 0,3870 | -0,0025 | -0,0982 | 0,1600 | 0,0117 | -0,0638 | 0,3790 | -0,0030 |
| reg9 | 0,4654 | 0,0485 | 0,1173 | -0,3156 | 0,4500 | -0,0309 | | | |
| reg10 | 0,2501 | 0,0028 | 0,0801 | 0,2447 | 0,0010 | 0,1111 | -0,1193 | 0,0099 | 0,0763 |
| reg11 | -0,0480 | 0,6410 | -0,0081 | -0,2114 | 0,0486 | 0,0342 | -0,2772 | 0,0186 | 0,0617 |
| reg12 | -0,1094 | 0,5250 | -0,0460 | -0,2098 | 0,9210 | -0,9695 | | | |
| reg13 | -0,0718 | 0,5200 | -0,0060 | -0,2949 | 0,0119 | 0,0618 | 0,1849 | 0,1590 | 0,0139 |
| reg14 | -0,0270 | 0,7870 | -0,0096 | 0,0245 | 0,8520 | -0,0115 | -0,2144 | 0,1260 | 0,0188 |
| reg15 | -0,0525 | 0,6160 | -0,0078 | -0,0534 | 0,6400 | -0,0093 | -0,0009 | 0,9940 | -0,0139 |
| reg16 | 0,2987 | 0,0041 | 0,0731 | -0,1602 | 0,2040 | -0,0075 | -0,2908 | 0,1930 | 0,0099 |
| reg17 | -0,5307 | 0,0001 | 0,2765 | -0,0599 | 0,6781 | -0,0235 | -0,0631 | 0,7380 | -0,0383 |
| reg18 | -0,0468 | 0,6710 | -0,0115 | 0,0264 | 0,6520 | -0,0134 | -0,1164 | 0,0689 | 0,0489 |
| reg19 | -0,3156 | 0,2640 | 0,0079 | -0,7935 | 0,0098 | 0,2243 | -0,6469 | 0,0003 | 0,6762 |
| reg20 | -0,5390 | 0,0002 | 0,2274 | 0,0304 | 0,8750 | -0,0244 | 0,6015 | 0,0136 | 0,1701 |
| reg21 | | | | | | | | | |
| reg22 | -0,0327 | 0,8440 | -0,0204 | 0,1336 | 0,1390 | 0,0346 | -0,3914 | 0,0000 | 0,6200 |
| reg23 | -0,3075 | 0,1240 | 0,0396 | -0,3523 | 0,2370 | 0,0195 | 1,4027 | 0,0384 | 0,2738 |
| reg24 | 1,0462 | 0,1265 | 0,1262 | | | | | | |
| reg25 | -0,2351 | 0,1160 | 0,0647 | -0,2834 | 0,4180 | -0,0234 | | | |
| reg26 | 1,6762 | 0,0000 | 0,6784 | 1,6022 | 0,0000 | 0,2231 | -1,8820 | 0,0390 | 0,0545 |
| | | | | | | | | | |
| | -0,8648 | | | -0,7935 | | | -1,8820 | | |
| | 1,67624 | | | 1,6022 | | | 1,4027 | | |

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