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The role of information efficiency in exchange rate forecasts: evidence from survey data

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To my daughter, Aurora, my wife, Eleonora and my parents

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THE ROLE OF INFORMATION EFFICIENCY IN EXCHANGE RATE FORECASTS:
EVIDENCE FROM SURVEY DATA

By

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Forecasting is a natural attitude of men and women: forecasts are made because to make certain decisions today, we need to know how the world will be tomorrow, and therefore how the future state of the world will influence the result of those choices. In finance, the term "forecast" refers to the expectations of individuals on the future trend of the variables studied, based on information or intuition, starting from the assumption that individuals have a good knowledge of the system in which they operate and political economy.

This dissertation is divided into four chapters.

In the first chapter there is an account of the existing literature that shows the principles of behavioural finance as a solution and development to the limits of the classical theory of which Fama was one of the major exponents, underlining the role that psychological

paradigms have, in the process that leads to the formulation of choices in the economic and financial field. This new conception discredited in the beginning made it possible to make up for the theoretical and empirical shortcomings that affirmed that individuals were always rational, demonstrating on the contrary that it is irrationality that dominates choices.

In the second chapter of this dissertation we analyse the role of revisions of the first forecasts or other revisions already issued, to determine in percentage terms whether the revisions are better, worse or equal. This allows us to determine the degree of efficiency of the predictors, whose investment choices, known in literature, are influenced in the short term due to market volatility, and in the long term by the difficulty of absorbing new information in a complete and timely way, using them to our advantage. It follows that the predictors analysed in the Bloomberg dataset available, which contains the historical series relating to the forecasts and revisions in euro-dollar currency, of 120 financial institutions, in the horizon from the first quarter of 2007 to the second quarter of 2016, show that in 15.87% of cases the revisions issued are not efficient, since the forecasts previously issued worsen.

This shows that predictors are not always able to improve their forecasts even if they get new information in the time path that leads to the terminal date for which the forecast was issued. Furthermore, to demonstrate that the predictors' forecasts are not efficient, we compared whether the number of cases in which the average quarterly forecast error generated by the 120 financial institutions is greater, in terms of absolute value, than a forecast based on a random walk model. The results, in accordance with pre-existing literature, showed that the percentage of cases in which the forecast errors generated by the difference between the predictors' forecasts for each period and the spot rate is higher than the forecast errors generated by the difference between the rate spot and the real value of the exchange rate generated at the end of each period. This shows that, in each horizon considered, the random walk model is more efficient than the forecasts provided by a professional predictor.

In the third chapter, we wanted to check and confirm whether the forecasts and revisions issued by each financial institution as a whole were efficient, or if, on the contrary, they had demonstrated that they had a long term memory of their past forecasts, which means that the choices and forecasts issued in the past by financial institutions influence future choices and forecasts. To do this we used the Hurst statistical test, developed in the early twentieth century, through which it was analysed that the average of the forecasts and revisions, for each predictor, in the horizon from the first quarter of 2007 to the second quarter of 2016, were for the 99.17% of cases not efficient, showing that the Hurst index value is different from the threshold of 0.5. Specifically, we find that 91.67% of predictors show that their past has an influence on their future. This allows us to say that predictors who have proved inefficient in the past will tend to be inefficient in the future as well.

Finally, in the fourth chapter of this dissertation we wanted to show if among the 120 financial institutions analysed there was a cause and effect phenomenon that allowed to demonstrate that the forecasts of one or more predictors systematically precede those of all, demonstrating the presence of a leader of the exchange rate market in euro-dollar currency. To analyse the historical series available, we have chosen to use the Granger causality test developed by Toda and Yamamoto in 1995. The results have shown that there is a cause and effect phenomenon among the Top 5 World Banks for assets and equity, according to the ranking updated in 2007, the year the analysis started. Furthermore, we find that the banks that in our analysis take on the role of market leaders, are the same that were fined by the European Antitrust Authority in 2019 for creating a real exchange rate cartel, in 11 types of different currencies, including the euro-dollar one. Furthermore, the existence of Granger causality among the banks that are inefficient according to the Hurst index and that have long term memory, allow us to say that among the financial institutions analysed there is a further trend to follow the so-called "Flock effect", which pushes people to standardize choices and forecasts, as the judgment of others is important and influences our rationality.

INTRODUCTION

Prediction is a natural attitude of men and women: we make predictions because to make certain decisions today, we need to know how our world will be tomorrow, and therefore how the future state of the world will influence the outcome of our choices. In finance, the word "prediction" refers to the expectations of individuals on the future trend of the variables studied, based on information or intuition, starting from the assumption that individuals have a good knowledge of the system in which they operate and of economic policy models.

Eugene Fama in the 1970s said that markets are efficient if the prices of traded securities reflect exactly their fundamental value, corresponding to the discounted sum of expected future cash flows. This theory takes into account the mere presence of rational investors, who evaluate their investments rationally, that is, they direct their choices towards those options that have higher expected returns, with the aim of maximizing their wealth. Likewise, even in the case of irrational investors, their exchanges, considered to be random, do not affect the price level, since the market tends to cancel them. Therefore, according to the theory of efficient markets, neither technical analysis nor fundamental analysis can allow an investor to generate a greater profit through arbitrage transactions, since the demand will always tend to match the offer and the price of the securities will incorporate correctly and promptly all the information available (perfect arbitration transactions)[1].

In reality, changes in the price of securities are not due solely to a change in the fundamental

1 See Fama, E. F. (1970).

value. The continuous alternation of euphoric phases and depressive phases that characterize the financial markets, have attracted the attention of a growing number of scholars who have begun to doubt the traditional theory of expected utility proposed by von Neuman and Morgenstern in 1947, according to which people with the same expected value, do not have choice preferences. In fact, contrary to what was previously believed, investors demonstrate different attitudes depending on whether the options to choose from generate a chance of gain or a risk of loss.

The psychologists Kahnemann and Tversky have developed a new concept of utility function that takes into account the aspect related to losses. The prospect theory was based on the personal propensity of each individual to bear a certain risk in the face of a given gain, since each individual has an aversion to different losses, which may depend on the status quo, the psychological state (happy or sad), or even just from an imaginary reference point, a sort of fixed point beyond which we are not willing to go, known in literature as the anchor bias[2].

Kahnemann and Tversky introduce purely psychological and social aspects in the evaluation of economic and financial factors, demonstrating that investors, in an attempt to maximize their expected usefulness, base their choices on a series of psychological paradigms, known as heuristics, which allow to simplify the decision-making process behind every investment choice. These "shortcuts of thought" are therefore very useful, but at the same time they are very dangerous, because they can generate cognitive errors or errors of judgment, because they push investors to make decisions about the outcome of future events on the basis of

[2] See Kahnemann D., and Tversky A. (1979).

known models of the past, believing that what happened before will be repeated in the future.

Hirshleifer D. et al. (2019), through psychological tests, have shown that the accuracy of the predictions decreases over the course of the day as the number of predictions that the analyst has already issued increases. This phenomenon known as decision fatigue shows that the more predictions an analyst makes, the greater the likelihood that the analyst will resort to heuristic-based decisions, which simplify the decision-making process.

The implementation of these mechanisms derives from the fact that investors make investment decisions in a context of uncertainty. Heuristics allows you to limit this uncertainty, but not to make the best choice. In literature, there are many studies of psychology that demonstrate the existence of prejudices that systematically influence our choices. Moreover, it has also been demonstrated the existence of a so-called "fashion" effect that is created among investors, who push to reduce the negative effects generated by a possible loss, if such a mistake in the choice has been reached by a plurality of individuals. That is, if everyone makes the wrong predictions, it means that it is an extraordinary event that no one could have foreseen or stopped. It follows that if the investment generates positive effects, investors will tend to unfairly increase their predictive skills (excess security), or vice versa, they will blame it on bad luck.

To demonstrate the existence of these irrational trends that dominate the process that leads to the formation of any expectation, in the economic and non-economic spheres, we have concentrated our analysis on the forecasts and revisions issued by 120 financial institutions on the exchange rate market, in the horizon from the first quarter of 2007 to the second quarter of 2016. The time series analysed, coming from a dataset extracted from the Bloomberg platform, have allowed us to demonstrate that the forecasts and revisions issued by the predictors are not always efficient. This implies that expectations are not always in line with classical theory, which is based on the concept of rationality, but on the contrary, shows that to understand its evolutionary process it is necessary to rely on the key concepts of behavioral finance, which violate the principles of expected utility.

We have shown that the historical series of the financial companies analysed, in addition to not being efficient, are characterized by "long term memory", showing that the past influences the future. This allows us to say that if the forecasts in the past were not efficient, they will not be efficient in the future and vice versa. In addition, we have also shown that the forecasts of exchange rates in euro-dollar currency are characterized by the presence of leaders who dominate the market, which allows us to affirm that the predictors are not independent, confirming and validating some interesting theories that confirm the existence of superior links between the main world banks, by volume of assets and equity.

The work is divided into four chapters.

In the first chapter of this dissertation we analysed the concept of market efficiency, showing the different classifications and the conditions necessary and sufficient for its occurrence. The efficiency is divided into three stages: weak efficiency, semi-strong and strong efficiency. In addition, we have reported an analysis of the literature that shows the multiple applications and studies that have used the concept of efficiency as a metric for their analyses, through the use of different macroeconomic variables. This first chapter also allowed us to establish the meaning of our analysis, which aims to demonstrate how the financial market is generally not efficient, due to the irrationality that characterizes the majority of individuals who approach financial markets, are they are professional or non-professional. Furthermore, the growing complexity of the markets allows us to confirm once again how individuals, both in making economic-financial and non-economic decisions, base their beliefs on a plurality of psychological paradigms that allow us to lighten and speed up the decision-making process that rotates behind every choice, violating the theory of expected utility, at the basis of classical theory[3].

In the second chapter of this dissertation, the dataset relating to the forecasts of exchange rates in euro-dollar currency, from 2007 to the second quarter of 2016, was analysed, with the aim of demonstrating that the revisions of the initial forecasts are not always efficient. This is because, as stated by pre-existing literature, predictors are unable to absorb new information in a complete and timely manner in the path that leads to the terminal date for which the forecast is issued. The analysis, conducted on the revisions issued by each predictor, with reference to the forecasts previously issued, has shown that both in the short term due to market volatility and in the long term due to the inability to absorb new information, there is a percentage of worsening forecasts which show that individuals are not always rational.

The model developed in our document considers forecasting errors as parameters for

[3] See Fama, E. F. (1970).

assessing investors' predictive ability. The forecast error was calculated as the difference between the forecast or revision and the spot reference rate for each period. This comparison allows you to measure whether the forecast error increases, decreases or remains unchanged over time in order to evaluate the efficiency of the predictors.

This function, constantly accentuated by uncertainty, causes an increase in forecast errors. It follows that, in theory, exchange rates are easier to predict in a long-term perspective, due to their tendency to return to their fundamental average value.

The results obtained showed that the revisions do not systematically improve the forecasts previously issued for the same terminal date, showing how individuals do not always make efficient choices. This means that predictors fail to learn from their mistakes and therefore fail to incorporate new efficient information. It was also shown that predictors would perform better, i.e. a prediction error in a lower absolute value, using the random walk model or by issuing a prediction equal to the spot frequency known at the time of the prediction.

In the third chapter, the Hurst statistical test was used to confirm that the forecasts and the revisions, as we saw in the first chapter, are not always efficient due to the difficulty of incorporating the new information in a complete and timely manner, in the path which leads to the terminal date, for which the forecast itself is issued.

This statistical coefficient, that moves within a range from 0 to 1, has been used as a metric to measure if the prediction time series, issued by each predictor of the Bloomberg dataset you have, are efficient. For this purpose, it is necessary that the test value for each analysed variable has a value of H = 0.5. The results of the application of the test reported in the table in Appendix A.3 have shown the existence of one predictor that has a value of H = 0.5, but, due to the limited sample size, this result is unreliable. Therefore, it can be said that the test results show that the forecasts of the intermediaries analysed in the long run, in line with the existing literature, are not efficient. Furthermore, using the idea used by Sukpitak et al. (2016), it was decided to measure the average deviation of the forecasts issued by the individual banks with respect to the efficiency value of the known Hurst index. Secondly, the same operation was also carried out for the average forecasts issued by the banks grouped by continent. The calculated difference will allow us to identify first which single bank and then which continent, have average forecasts closer to the efficiency threshold.

In addition, we also used the test to measure whether or not the variables analysed were characterized by "long term memory", a feature that allows us to understand whether the forecasts made in the past influence future forecasts. Therefore, if the value of H> 0.5, the series has the characteristic of "long term memory". On the contrary, if H <0.5, the past has a marginal influence on future forecasts. The idea is that every single prediction carries within itself a long memory of all the events that preceded it. Recent events have a greater impact than distant events, but the latter still have a residual influence. So, what happens today affects the future. Where we are today is the result of where we were yesterday. Time is important. The results obtained by applying the test with this second objective have shown with sufficient evidence (see table in Appendix A.3), that past forecasts influence future forecasts. What happened yesterday is important to understand what will happen tomorrow, but it does not allow predictors to reduce their forecast errors, and therefore to be efficient.

Finally, the aim of the fourth and final chapter of this dissertation was to demonstrate whether Granger causality exists among the financial institutions of the Bloomberg dataset available. To do this, we used the statistical test of Toda and Yamamoto (1995), which allows us to understand if there is a cause and effect relationship between the predictors. That is, in other words, we want to demonstrate whether, the behaviour of one or more variables influences that of all the others. This would allow us to understand if there are one or more leaders of the euro-dollar exchange rate market, whose forecasts "systematically" precede those of all the others.

This idea was created thanks to the results achieved in the third chapter of this dissertation, which prompted us to ask ourselves if the predictors, in issuing their forecasts, are autonomous or follow a different model. The reason for this question derives from the fact that the forecasts available from the Bloomberg dataset banks are 99.17% inefficient. This result led us to wonder if there is a link between the inefficient predictions of all the predictors analysed. It would be interesting to be able to confirm the results achieved by a group of researchers from the Federal Institute of Technology in Zurich, Switzerland, who, analysing the transnational relationships between 43,030 multinational companies, have shown that there are 147 companies, mainly banks, called "superentities", which collectively hold 40% of the total wealth of the entire network of transnational exchanges (see table Appendix A. 5).

Furthermore, it would be even more interesting to be able to confirm the existence of a link between the banks that have been fined by the European Antitrust Authority for having created a real cartel on exchange rates in euro-dollar currency and not only. The ensemble of these motivations therefore prompted us to undertake this analysis, which with great satisfaction proved to be positive, showing that there are banks that act as market leaders and that systematically precede the forecasts of all the other predictors. Furthermore, the most important result was to find that the banks that act as leaders are the same ones that were sanctioned by the European Antitrust Authority in 2019.

Therefore, the tendency to formulate inefficient forecasts is not only a direct consequence of the inability of individual predictors to absorb new information, or of the heuristics that influence the outcome of our choices, accentuating their prediction error, but rather there is a phenomenon of cause and effect that pushes predictors to uniform behaviour, aimed at following one or more market leaders.

CHAPTER I

The efficiency market hypothesis.

The term efficiency is used to describe a market in which all available information is integrated into the price of financial assets traded in a rational and timely manner (EMH). This assumes that it is impossible for investors to achieve higher returns without having to bear equally high risks. According to Fama (1970) there are three conditions for an efficient market:

- operational efficiency, which concerns the organizations and procedures through which the market operates, which must be able to run smoothly, without obstacles of any kind, such as transaction costs;
- allocative efficiency occurs when all individuals act rationally pursuing the maximization of their utility;
- information efficiency occurs if prices reflect the available information promptly and correctly, and nobody is able to obtain returns above the market.

These conditions of market efficiency according to Fama (1970) show that information plays a key role in determining the price level. These conditions are sufficient and unnecessary to have an efficient market, since it is possible to have high brokerage costs which are not accessible to everyone, but which reflect all the information available. Similarly, if the information is not freely accessible to all market players or if it has a different interpretation, this does not mean that the market must be inefficient. These imperfections are only potential sources of inefficiency and can be found, at various levels, in real markets.

To understand the concept of efficiency of the financial markets it is necessary to carry out a triple classification, which differs according to the degree of intensity with which the new information is incorporated in the prices. So, in detail we can talk about efficiency in weak form, in semi-strong form and in strong form. The three levels of efficiency are classified in Fama (1991) based on the information used in defining them.:

- A market is characterized by weak efficiency when the prices that are formed gradually incorporate all information relating to past prices, making it impossible to create extra profits. Furthermore, prices are said to follow a random pattern over time, which means that prices are not temporally related;
- The second definition of efficiency with which the market can be invested is semi-strong efficiency. This definition enriches the concept of efficiency explained above, stating that prices promptly and completely reflect all past information and all public information. This means that arbitrage operations cannot be carried out on the basis of this information, unless there are subjects able to position themselves at a privileged level compared to other investors in the same market, since they are aware of privileged information, which can create information asymmetries;
- Finally, the third definition of efficiency refers to those markets where the prices of the securities traded reflect all past information, all public information and, moreover, all inside and / or private information. Pursuant to art. 181 of the TUF, this type of information significantly affects the prices of financial instruments, to the point of considering them as information that a reasonable investor would presumably use as

one of the elements on which to base his investment decisions. Theoretically, a strong market could give the illusion that the prices of the securities traded in it are always correct. In reality, this seems to be as little as possible and the definition must be interpreted flexibly, allowing for time intervals, which technically allow for price adjustments. Furthermore, the expression "correctly" must be interpreted as meaning "not systematically distorted".

This classification leads us to make some reflections. In the event of poor market efficiency, professional investors who are able to exploit public information or who have private and / or privileged information can make an additional profit. In the case of markets characterized by semi-strong efficiency, only insiders can use privileged information to generate operations that generate an extra return. Finally, in the case of a market with strong efficiency, no market operator, qualified or unqualified, is able to generate a greater profit than others. It follows that in cascade, efficiency in the strong form implies the semi-strong form and in turn the weak form, and the semi-strong implies the weak.

In an environment where asset prices reflect all the information available, it becomes impossible to beat the market: some investors cannot get higher returns than others, since they all have the same information. Prices promptly and completely reflect all the information available to market participants. It follows that prices are correctly integrated into an efficient market. The price at which the securities are traded is the correct price. There are no overvalued or undervalued securities and arbitrage operations are not feasible. Investors can only aspire to replicate market profitability - based on passive management - or, at best, to achieve greater profitability, sporadically and always in the short term, thanks to luck or because they have been able to take advantage of some occasional inefficiencies before the market took them into consideration.

According to Andrei Schleifer (2000)[4], three conditions are at the basis of the Efficient Market Theory:

- rationality: the investments required to make rational investment decisions, evaluating the securities of the market on the basis of their fundamental value;
- independent deviations of rationality: even in the presence of non-rational agents, market efficiency can be achieved, because rational individuals are assumed to counterbalance irrational individuals;
- arbitrage: profit is generated through the simultaneous purchase and sale of different, mutually substitute shares. The arbitrageurs, in fact, buy an advantage because the price is lower and resell it where it is higher, trying to get a profit in the difference between these two.

According to M. Friedman (1953) and then E. Fama (1970), the presence of irrationality among economic agents does not mean that the market is also inefficient. The authors argue that rational investors (also called smart money) are able to restore the balance of the market, cancelling the choices of irrational agents. Therefore, from a theoretical point of view, the random transactions of irrational agents deviate the price of the securities from its

[4] See Schleifer A. (2000).

fundamental value causing information inefficiency: the price is no longer able to fully reflect the information associated with the title. The presence of rational investors makes it possible to eliminate this inefficiency by promptly restoring the efficiency of price information. Each transaction (purchase) made by an irrational individual corresponds to another (sale) of a rational individual and vice versa, which leads to keeping prices and the market unchanged.

Looking closely at the evolution of the markets, it emerges that the theoretical lines underlying the theory of the “efficient markets” are not always respected, as the markets are not always efficient and easy to predict, but on the contrary they present risks, for market operators, professionals or less, which lead to incorrect predictions. There is a strong tendency to make mistakes in an attempt to accurately predict the price at which the securities will be traded. The causes can be manifold, such as the difficulty of incorporating new information in a correct and timely manner, the impossibility for all operators to have the same information or the mathematical principles deriving from quantum physics. The mere fact that the market determines the price of a company, in the form of an offer, also changes its intrinsic value, directly influencing the company's competitive environment. These characteristics make the financial markets unstable and inefficient.

In literature there are numerous studies that have tried to test the efficient market hypothesis (EMH) of Fama (1965; 1970), using various methods and contexts. These reports examined not only whether asset prices reflect all relevant historical information, but also whether the arrival of new information is immediately and fully incorporated into the prices of the securities.

Among these we can mention the results of the autocorrelation tests conducted by Samuels and Yacout (1981), who by testing the efficiency in the weak form of twenty-one securities listed on the Nigerian stock exchange from 1978 to 1979, have shown that there is no random behaviour of the share price and that the Nigerian stock market is weak form efficient.

On the contrary, however, Fawson, Glovher, Fang and Chang (1996) conducted unit root tests on the securities of the Taiwanese stock exchange from 1967 to 1993, demonstrating the existence of poor efficiency of the weak form. Similarly, the results of the analysis carried out by Moustafa (2004) on the securities of the United Arab Emirates from 2001 to 2003, which showed the absence of a normal distribution, also followed. Similar results also for El-Erian and Kumar (1995), who carried out serial correlation tests on the equity markets of Turkey and Jordan showed the absence of poor efficiency of the weak form.

Another study by Barnes (1986) conducted on the Kuala Lumpur stock exchange revealed the absence of the efficiency of the weak form. However, the research conducted on the Shanghai and Shenzhener exchanges, by Darrat and Zhong (2000), applying the variance ratio test and the model comparison method, showed that there is no efficiency in weak form.

Another study conducted by Cooray and Wickermaisgle (2005) on the exchanges of South Asian securities of Bangladesh, India, Pakistan, applying the unit root test and the Elliot-Rothenber-Stock (ERS) test, showed that the Bangladesh stock market is not performing weakly. Similar studies have also been carried out by Mobarek and Keavin (2000), on the

Dhaka stock exchange, from 1988 to 1997 and through the use of parametric and nonparametric tests have demonstrated autocorrelation to different delays that reject the existence of a weak efficiency form.

A further study was carried out by Abraham, Seyyed and Al-sakran (2002) on the securities of Kuwait, Saudi Arabia and Bahrain, which rejected the hypothesis of random walk. A similar study was carried out by Magnusson and Wydick (2002) on the stock exchange of Nigeria, Ghana and Zimbabwe demonstrating significant correlations indicating the absence of efficiency of the weak form.

Another study to test efficiency in weak form was conducted on the Bombayay Stock Exchange and on the National Stock Exchange of India, by Basu dan Gupta (2007), who, taking daily data from 1991 and 2006, applied tests of unitary roots called ADF, PP and KPSS, which have shown how the national stock exchange and the Bombay stock exchange are not efficient in terms of weak form. Similar studies have also been conducted by Awad and Dartigma (2009), which through the Augmented Dickey fuller Test, Phillips-Perron test, unit root test, serial corrections and execution tests, found the absence of weak efficiency form on the stock exchange prices of Palestine. Furthermore, Hoss-ain and Uddin (2011), through autocorrelation tests, the increased Dickey Fuller test, Phillips Perron test, ARIMA models and GARCH models, have also tested the efficiency in weak form on the Dhaka stock market indices, finding absence of efficiency in weak form. Finally, Siddik and Azam (2011), Ali (2012), Alom and Raquib (2014) also demonstrated the lack of efficiency in weak form on the values of the Bangladesh stock exchange.

Other studies such as those of Givoly and Lakonishok (1980), Stickel (1991), Engels et al. (2001), Gleason and Lee (2003) and Zhang (2006a, 2006b), have shown that if a market is efficient, the price of securities must reflect all available information in a complete and timely manner, and investors can actively trade on the basis of this hypothesis, aware that prices should respond immediately to the analysts' forecasts and there should be no possibility of generating an extra profit after the revisions of the forecasts have been made public. But this trend, as widely demonstrated, occurs rarely.

In fact, the new information is not perfectly reflected in the share price. This can be caused by irrational behaviour, such as insufficient reaction (Chan et al. 1996), investor's propensity to conservatism (Barberis et al. 1998), explanation of risk adjustment (Conrad and Kaul 1998) or explanations from the market environment, such as short selling constraints (Diether, Malloy and Scherbina 2002). Furthermore, as Kang et al (2016) say, investors' reactions to the revision of analysts' forecasts also differ according to the investment horizon, since there may be short-term investors who have a keen interest in the information involved in the revisions of analysts' forecasts, and investors with long-term horizons who are neutral towards such information. Therefore, if the markets appear to be inefficient, the economic agents who have more information will be able to earn compared to the less informed. It should also be said that if the mechanism by which the price is determined, in a market, is inefficient, the price of the securities will not reflect its fundamental value, generating estimation problems with reference to economic analysis.

Another aspect that must be taken into account, when investigating the efficiency of the financial market, are the expenses that must be incurred to investigate the precise moment in which the news stops, which can be known to everyone, or only to some of the economic agents involved. Finally, it must be taken into account that the efficiency tests that are carried out on the financial markets can be influenced by loss of information and asymmetries.

The existence of these discrepancies between the market described by Fama (1970) and the real performance of the financial markets, lead the academics of the time to question the accuracy of the theoretical principles underlying the efficient market hypothesis, laying the foundations for the development of a new branch of finance, called behavioural finance. This new theory presents itself as an interdisciplinary study, capable of integrating psychology and sociology in the study of the behaviour of economic agents, going against the paradigm of the absolute rationality of the EMH.

The pioneering studies of the psychologist Slovic P. (1962-1972), represent the starting point of numerous subsequent researches, which began to analyse the wrong perception of risk by subjects. Through this vision, it was demonstrated that the decision-making process that leads to the maximization of utility, for each individual, is not rational. Investors, in an attempt to maximize their profits, are emotionally influenced by a series of psychological paradigms, known as "heuristics", which push them to violate Bayes' law and other principles of probability theory in making predictions in uncertain situations[5].

[5] Bayes' formula essentially asserts that the conditional probability of an event A, given B, also called posterior probability of A, is proportional to the likelihood of B, if A were known, for the a priori probability of A; in formulas: P (A / B) ~ P (B / A) P (A).

According to Kahneman and Tversky (1974), these shortcuts of thought, on the one hand, simplify the resolution of a problem, but on the other they expose the individual to errors, known as cognitive biases. In psychology they indicate a tendency to create one's own subjective reality, not necessarily corresponding to the evidence developed on the basis of the interpretation of the information in possession, even if they aren't logically connected to each other. This therefore leads to an error of assessment, caused by lack of objectivity of judgment.

Kahneman e Tversky (1974), Slovic (1971)[6] argue that the assessment of the probability with which a given event occurs is a complex activity, which is transformed into a simple operation through the mental process of each individual, creating connections with past events, stored in memory. However, this ability to store memories has a limited duration, which tends to generate errors. Therefore, assuming that any decision problem can be broken down into three steps: gathering information, processing and issuing the forecast, we report the main heuristics, which characterize the process of forming a final choice, in the economic-financial area:

- Availability heuristics: estimates the probability of an event based on the information "available" in the memory, on the basis of direct or indirect experience, and on the emotional impact that the memory generates. The problem with this shortcut of thought, as well as the others, is that they tend to be misleading. Availability heuristics is a cognitive strategy that individuals use to give a satisfactory estimate to an event, in the shortest possible time and with

[6] See Slovic e Lichtenstein (1971)

minimal effort. A typical example is that of a plane crash, which due to the strong emotional impact generates stronger memories in the minds of individuals, compared to statistics on the number of road accidents in a given period of time. The availability of this information in memory pushes individuals to estimate misleading probability, which generates a distortion in the cognitive process, leading to believe that the percentage of deaths in a plane crash is higher than that of other means of transport. However, this judgment is objectively incorrect, as shown by the real estimates of the two phenomena;

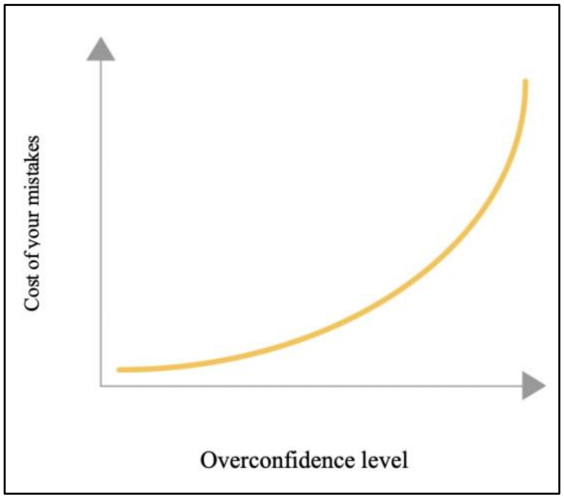
- Representative heuristics: this occurs when individuals, in an attempt to speed up and simplify the analysis of a problem, estimate the probability of an event based on family situations and stereotypes, associating the event with past or preconceived experiences. Regardless of the frequency and number of examples, the evaluation of the probability of the event depends on how similar it is to a certain class of events. A typical example is that of a person's description: “Paul is very shy and introverted, with little interest in people and in the real world. He has a sweet soul and has a passion for detail." After this description, the individuals are asked to evaluate the probability that Paul is a worker, a professor, or a librarian, or if the probability is the same in the three cases? Individuals will tend to indicate that its characteristics refer to the stereotype of the librarian, basing the judgment on similarity, representing the problem subjectively. Clearly, with this excessive simplification, numerous errors of assessment are made, because objective factors such as, for example, the employment rates in the professions listed should be analysed. In fact, Paul is more likely to be a worker, since workers are much more numerous than librarians;

- Anchoring and adjustment heuristics: this occurs when individuals draw up an estimate or forecast judgment based on an initial value or starting point and reach the final answer by improving the forecast through "adjustments". “The starting point can be suggested by the formulation of the problem, or it can be the result of a partial calculation. In both cases, the adjustments are "insufficient", as the initial value acts as an anchor and slows down subsequent adjustments. Anchoring heuristics was first theorized by Amos Tversky and Daniel Kahneman, but there are many examples of experiments in literature. One of the most famous is that of a group of people who were to estimate in percentage how many of the states that are part of the United Nations are African. To some, with a kind of wheel of fortune rigged, the number 10 was shown, and to others the number 65. The percentage estimated by those who saw the number 10 (on average 25%) was always lower than that estimated by those who saw the 65 (on average 45%);

  Another example used to explain the anchor heuristic is that proposed by Wilson et al. (1995): “Participants were asked to estimate the number of students who will get cancer over the next 40 years. Previously, half of the participants had been asked to copy numbers in words close to 4500 and the other half had been asked to write numbers in figures close to 4500. Those who had copied numbers in figures predicted an average of 3145 cases, while those who had copied numbers into words predicted an average of 1645 cases;

- Overconfidence: represents an excess of security in one's judgment and skills. Individuals believe they can take advantage of all the information they know of, overestimating that information. This leads individuals not to accept that they are wrong, but on the contrary, pushes them towards the search for information and motivations that justify their wrong choices. This type of error alters the knowledge related to one's own abilities, causing in the subject itself a sort of overestimation of himself. In addition, overconfidence has been shown to occur more in men than in women and at a young age, while it tends to decrease with the passage of time, as individuals with the acquisition of more experience develop a more objective evaluation process of one's abilities. Therefore, it is not a question of being more or less intelligent than others, but only of a greater conviction that is extreme and makes us think we are the best. This belief pushes individuals, faced with a significant loss, to motivate the error as the consequence of external causes or bad luck. Vice versa, in front of a profit, they take all the credit, increasing confidence in their own abilities. Odean (1998) developed a theoretical model in which he demonstrated that, in contrast to what classical theory claims, the expected utility decreases, showing that being too informed can be dangerous;

Figure 1 - Overconfidence increases over time



Source: Author's own

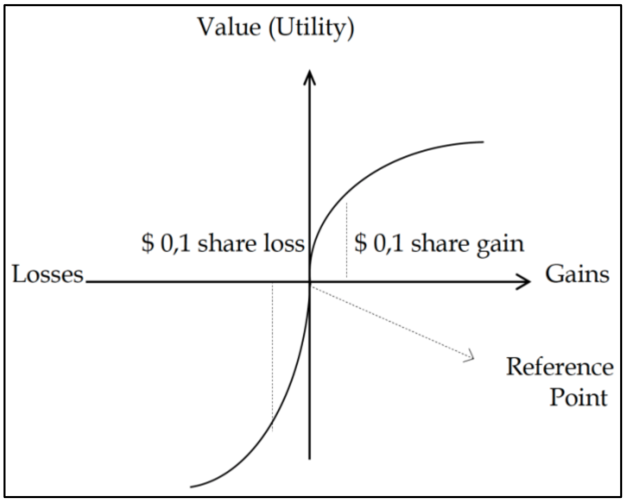
- Under-confidence: occurs when investors have an excess of distrust in their forecasts and tend to underestimate their skills. This phenomenon tends to occur in situations where the choice to be made is very complicated and uncertain. Investors carry out conservative attitudes and show an overly slow adjustment of the forecasts when new information arrives. In order to better understand the meaning of this heuristic, it should be specified that the phenomena of overconfidence and under-confidence are not correlated with the terms of optimism and pessimism, in fact, the excess or lack of trust in one's choices does not necessarily imply the optimism or pessimism about the market outlook;

- Overreaction: occurs when individuals show an excessive and overly optimistic reaction to the availability of new information regarding certain securities on the market. Consequently, investors will be excessively influenced by random events, generating a variation in the prices of the securities of the period following the publication of the new information, which will no longer reflect the fundamental value of the securities. According to De Bondt and Thaler (1985), the irrational investor has an excess of optimism in the initial period, which is followed by a turnaround in the long term which brings the price of the security back to its correct value. This behaviour of investors is in contrast with the hypothesis of efficiency of the financial markets, and can be caused by the representativeness mechanism that intervenes in the decision-making process of the individual or by the subject's overconfidence, and is favoured by imitative behaviour;

- Underreaction: occurs when the arrival of new information on specific security is only partially transferred to purchases / sales, generating an under-reaction of the investors. The prices of the securities, after the release of new information, will tend to move slowly compared to the ordinary. This phenomenon has a shorter time horizon than overreaction, even if in the long run the prices of the securities will tend to return in parity with their fundamental value. According to Edwards (1968), the sub-reaction is due to conservative behaviour, which involves a slow updating of expectations in the face of the arrival of new information.

Kahneman and Tversky (1979) through the publication of the "Prospect Theory" defined it as a rational theory, capable of explaining irrational behaviour, due to the profound change, that has led the way of studying decision making. It shows that individuals behave irrationally every time they are called to maximize their expected utility, as they assign a different value to a loss or a potential gain, because they will tend to have a different attitude towards the associated risk.

Figure 2 - Value function



Source: Kahnemann D., and Tversky A. 1979.

The concept of "value function", similar to the definition of "utility function", but with the addition of the part relating to losses (see Figure 2), shows a concave curve in the gain area and a convex curve in the area of losses. This means that people will show a marginal sensitivity to gains and losses, which will decrease as they move away from the reference point, which can be represented by the current position or status quo. People will experience greater pleasure for a $ 20 wage increase when wages rise from $ 20 to $ 40, than when wages rise from $ 1020 to $ 1040[7].

Therefore, contrary to the theory of expected utility, according to which an individual placed in front of two "lotteries" with equal expected value is indifferent between choosing one lottery or the other, they found a different type of choice in individuals depending on whether

[7] See Kahneman D., Tversky A. (1984)

the two options with the same expected value had as their object a possibility of gain or a risk of loss. To better understand this concept, we give an example. To demonstrate that individuals are risk averse we report these two situations. The first offers the possibility to choose between two alternative options with the same expected value, one of which with certainty of gain, the other random but with the possibility of greater gain:

- equal chance of winning € 500 or nothing. Current value = 500 * 50% + 0 * 50% = € 250;
- definitely win € 250.

Usually individuals choose the second option, showing a risk aversion attitude. In the second situation, the individual has the possibility to choose between two options, always with the same expected value, but one with safe loss, the other random with greater risk of loss, two options:

- equal probability of losing € 500 or nothing. Current value = -500 * 50% + 0 * 50% = -250 €;
- definitely lose € 250.

In this case, contrary to the previous situation, the individual tends to choose the first option.

Herbert Simon (1978), in his theory of "Limited Rationality", argues that individuals are not always rational and for this reason they are not able to maximize their expected usefulness, even if they have the necessary knowledge and information. This shows what Kahneman and Tversky (1979) said, who said that in a loss situation the individual's attitude will be risk-taking[8].

Richard Thaler, winner of the Nobel Prize for Economics in 2017, said that the intuitive system of individuals, in these cases precedes the reflective and rational system, conditioning the maximization of the expected utility. According to the Nobel Prize, for individuals, the unhappiness caused by the loss of something is double compared to the happiness due to the gain of the same object. Furthermore, the difficulty of selling securities that are generating a loss is due to having to admit their mistakes to themselves and others. The force with which the behavioural finance theory has exposed and implemented the concept of irrationality, showing that individuals are not crazy, but that they only have a different view of the same investment option due to their personal risk aversion, is due to its ability to create a union between theory and empirical evidence.

[8] See Kahnemann D., and Tversky A. (1979).

CHAPTER II

Quantitative analysis of the first predictions: better, worse or equal revisions?

2.1 Literature Review and hypotheses development

In the last thirty years behavioural finance has been the subject of important studies and applications in both the economic and financial fields. The topic of rationality has been analysed in many respects thanks to the use of macroeconomic variables such as GDP, inflation and exchange rates. The development of this line of thinking that distances itself from the classical economy has allowed us to face issues that in the past would have been labelled only as irrational. Furthermore, it is very important to understand why both professional and non-professional investors show behaviours that do not tend to the traditional concept of rationality in decision making, introduced in literary history for the first time by Muth (1961). According to Muth (1961) the expectations of economic agents with reference to an investment opportunity should be in line with the mathematical expectations based on the real probabilistic calculation, which aim to achieve the best possible best in terms of expected utility. In order to obtain these results, however, it is necessary that the investment choices are always based on a complete information set, where the price of the shares reflects at any time all the useful and necessary information in order to make the best possible choice on the market.

According to Cavaglia et al. (1993), exchange rate forecasts are not rational, as agents do not use all available information efficiently. This analysis was carried out on a series of data based on exchange rate expectations taking as a reference point the differences between the expectations on the exchange rates of the European Monetary System and the US dollar. The results achieved by this study questions what was said years before by Frankel and Froot (1987), who considered the rationality of expectations directly proportional to the sampling period considered. Furthermore, Cavaglia et al. (1994) argued that through the decomposition of the change in unexpected movements on exchange rates, a change in the perception of risk premiums occurred, causing a greater fluctuation of the advent of news in the time path leading to the terminal date for which the forecast is carried out[9].

In order to analyse the rationality of expectations, according to Pesaran (1987), the conditions of impartiality and orthogonality must be verified, allowing respectively to understand whether the expected exchange rate is a good predictor of the future spot rate and whether agents use available information efficiently to forecast future exchange rates. According to Esterwood and Nutt (1999) the orthogonality condition allows one to evaluate the existence of forecast errors and if the distortion is constantly identified in a certain direction. Once again, the contributions of Dominguez (1986) and Frankel and Froot (1987) employ the survey data on the expectations of professional predictors, obtaining clear empirical results in contrast with the hypothesis of impartial forecasts. Following the same lines, Chinn and Frankel (1994), who discovered that for the main currencies a casual walk wins in a competition against the previsions of professional forecasters, provide a result consistent with the influential contribution of Meese and Rogoff (1983a, b, 1988).

[9] See Cavaglia, S.M.F.G., Wolff C.C.P. (1996).

Further studies tend to find evidence of irrationality and no predictive ability to predict the professional exchange rate. For example, Dominguez (1986), Frankel and Froot (1987), Avraham and Ungar (1987), Cavaglia et al. (1993), Chinn and Frankel (1994), MacDonald and Marsh (1994), and more recently Cavusoglu and Neveu (2015) demonstrate through a regression of the real depreciation on expected depreciation, that expectations on exchange rates based on polls are distorted. Jongen et al. (2008) affirm that the hypothesis of impartiality is rejected in almost all currencies and forecasting horizons. Takagi (1991), MacDonald (2000) and Jongen et al. (2008) agree that the literature on expectations based on exchange rate surveys is not rational and has limited predictability.

Nordhaus (1987) argues that the revision of a prediction made for an uncertain future event and its potential predictive error should not be correlated with the previously realized predictions, but rather, should assume a behaviour called random walk. On the contrary, however, the results of this study show that the revisions of the forecasts are correlated in most cases with the previously published forecasts, especially if it refers to individual professionals in the economic and financial sector. Other studies document predictable errors in analysts' forecasts, including Abarbanell and Bernard (1992), who say that forecasts underreact to information on previous earnings. According to Lys and Sohn (1990), forecasts do not react to returns. Shane and Brous (2001) claim that forecast revisions have a positive correlation with subsequent forecast errors.

Furthermore, according to Ashiya (2006), the basic idea is that a rational expert should use the available information efficiently, so the forecast error should not be correlated with the information available at the time of the forecast and a planned revision should not be related to the information available at the time of the previous forecast. The first important contributions in this sense are due to De Bondt and Thaler (1985, 1987, 1990). They have shown that in the psychological field there is a strong correlation between the predictions for a future event and what happened in the past. In particular, as far as professional analysts who predict share prices are concerned, an overreaction to new, negative and unexpected news has been demonstrated if the reference companies have historically put in place non-optimal behaviour.

These results reflect those of Ehrbeck and Waldmann (1996), Abarbanell and Bernard (1992) and Amir and Ganzach (1998), according to whom analysts react disproportionately to new information. According to Clements (1995, 1997) and Brown (2001), investors cannot exploit all the new information available to their advantage, because they cannot extract from the characteristics of the forecast analysts all the information necessary to improve their forecasts. Recent studies have shown that forecasts are influenced by behavioural bias. According to Ashiya (2002, 2003) analysing the data of the International Monetary Fund (IMF) and the Organization for Economic Cooperation and Development (OECD), shows how economic individuals often react exaggeratedly to new information in the time path that leads at the terminal date for which the revision is carried out, i.e. when the resolution of the uncertainty occurs.

Another phenomenon known to literature thanks to the studies of Tversky and Kahneman (1981) and Arrow (1982), Scotese (1994), Loungani (2001) and Harvey et al. (2001), regards the tendency of people to absorb new information, good or bad, slowly. According to these studies the new information is not absorbed promptly, such that, forecasts do not reflect in a positive or negative sense the potential surprises that the market can give. Other important studies in this sense have been dealt with by Berger and Krane (1985), who have tested the information effectiveness of the forecasts on the nominal and real gross national product. Their results showed once again that revisions to these forecasts are predictable in most cases only by examining previous forecasts, highlighting how new forecasts fail to fully incorporate all available information.

In the wake of these results, Chia-Lin Changa, Bert de Bruijn, Philip Hans Franses and Michael McAleerc (2013), have developed a methodology that explains the tendency to evaluate revisions of fixed event forecasts by analysing the gap created between a forecast at time t-1 and a revision of the same forecast at time t. However, it emerges that, as already stated by other studies mentioned above, this condition rarely occurs, giving rise to levelling or hyper-reaction phenomena. The blame for these distortion effects must be attributed to most cases in the process that governs intuition and news but is subject to shock. According to Isiklar and Lahiri (2007), the predictors should deviate from the anchoring behaviours that push them to rely too much on a single piece of information when making a decision and keep their initial forecasts for too long. Forecast variability should decrease as you approach the final result, but this could only happen if the predictors provide increasingly accurate estimates as new information is available, in the time path leading to the terminal date, where take place the resolution of uncertainty. Bruno Deschamps, Christos Ioannidis and Kook Ka (2019) also say that the forecasts do not incorporate all the financial information received in equal measure, which implies the presence of information rigidities in the integration of information on credit spreads.

In our work we will use a newly available data set of explicit forecasts on the euro-dollar exchange rate, made by forecasting experts, to evaluate the efficiency of exchange rate forecasts. An important feature of our data set is the presence of a very large number of forecast revisions, i.e. cases in which the author of a forecast has released more than one prediction for the same terminal date. The revisions of the forecasts are interesting because they offer the unique opportunity to check whether large banks and financial institutions incorporate new information efficiently by examining and adjusting their estimates of the future value of the currency, while time progresses towards the terminal date and new information arrives (Easterwood and Nutt, 1999). This dataset shows a very heterogeneous set of data, both in terms of the number of predictions, and of forecasting horizons themselves, which allow us to explore how the forecaster behaves in the time path that leads to the terminal date, when the resolution of the uncertainty occurs.

The model developed in our document considers forecast errors as parameters for the evaluation of investors' predictive capacity. The results are in agreement with Beckmann and Czudaj (2017), according to whom, by their nature, exchange rates have greater short-term volatility. This feature, constantly accentuated by uncertainty, causes an increase in forecasting errors. It follows that the exchange rates shown by Mark (1995), Taylor and Sarno (2004) are easier to predict in the long term, due to their tendency to return to their fundamental average value. On the same line of thought, Rossi (2013) affirms that the degree of predictability of the exchange rate depends on the horizon, the currency and the model.

We find that the predictors would have obtained a better performance, that is a forecast error in lower absolute value, using the random walk model, or issuing a forecast equal to the spot rate known at the time of the forecast. This once again confirms the result of Meese and Rogoff (1983), and more recently Beckmann and Czudaj (2017), according to whom a random path overcomes structural theories in forecast rates outside the sample, since the market models of exchange activities are not empirically relevant, and in any case, it cannot improve random walk forecasts.

Kamil Kladivko and Pär Österholm (2019), analysing the financial variables in the Prospera survey commissioned by Sveriges Riksbank, one of Sweden's most important economic surveys, have shown that market participants' forecasts are able to significantly outperform random walk on a short-term horizon. However, in accordance with what was previously stated by Beckmann and Czudaj (2017), random walk significantly exceeds the market participants in a medium-long term perspective. Another interesting study demonstrating how revisions tend to worsen previously issued forecasts, was carried out by Singleton C. et al. (2019) on a fixed number of matches in the English football league (Premier League). They demonstrated how predictors worsened their initial predictions as the event (the start of the game) approaches and new information is made available.

Our contribution enriches existing literature by focusing on review efficiency. Other studies that used revisions as a metric to evaluate efficiency are due to Boero et al. (2008) who analyzed inflation and GDP growth forecasts provided by individual respondents in the Bank of England's quarterly external forecast survey, 1996-2005. Dong W. Cho (2002) also follows the same line of thought, taking into account the forecasts and revisions relating to exchange rates.

Another very important element that innovates pre-existing literature in our contribution, is that the number of revisions released is unlimited, therefore each predictor can review his initial forecast whenever he deems it appropriate until the final date for which the forecast is issued. The concepts of predictive efficiency for the prediction of fixed events have been introduced by Nordhaus (1987), according to which a sequence of predictions of fixed events is weakly efficient if the revisions of the forecasts are independent. In this regard, Clements (1997) has shown how the grouping of different revision sequences can overcome this difficulty. The forecasts have been revised in response to the latest news, but it is only the surprise news component that is relevant, because a previous forecast has already incorporated the predictable news component, if it is efficient. This leads to the notion of high efficiency, that forecast revisions are independent of the information used to build the previous forecast. This is more difficult to test, as the complete set of weather information is not known to the researcher.

Furthermore, unlike Dong W. Cho (2002), who develops an evaluation model of expectations based on only two observations per forecast horizon, using as a benchmark the mean or consensus value of all participants in the survey, in our model, the benchmark is the spot rate.

And finally, a further innovation concerns the moment of emission, which unlike the studies known in literature up to now, does not take place simultaneously. It follows that the set of data with which we work appears to be highly irregular, and contrary to what Capistrán and López- Moctezuma (2014) and Capistran and Timmermann (2009) have stated, the lack of standardization does not create a gap in the data set. On the contrary, this feature allows us to focus on an aspect that differs greatly from previous literature, since in most cases the data set analysis is constant, i.e. the release date of the forecast or revision is the same for all. Therefore, the non-standardization increases the difficulty of evaluation and for this reason the standard econometric tools cannot be used for the evaluation of the time series and for the interpretation of the results, as investors with a very different number of revisions cannot be compared directly.

The non-standardization of the data set allows us to evaluate the actual process that leads to the formation of expectations. The term "true" is justified by the fact that unlike what happens in laboratory experiments on expectations, the individuals analysed are not selected according to specific characteristics and do not all have the same information sufficient and necessary for carrying out the experiment. In fact, in reality, analysts of a financial institution do not have all the same initial information, the same predictive potential or the retrieval of sufficient and necessary information in order to make the best choice.

According to Scharfstein and Stein (1990), Lamont (2002) and Mitchel, Pearce (2007), the trend depends on the age of the predictor, even in the case of meteorologists. Young meteorologists tend to have a behaviour called "flock effect", because, still having a lot of uncertainty about their skills and the sector in which they operate, they adopt a behaviour that allows them to hide behind the mass. This phenomenon is linked to the analyst's "audacity", as stated by Scharfstein and Stein (1990), Trueman (1994) and Hong, Kubik and Solomon (2000). According to Hong et al. (2000), expert analysts produce audacious forecasts with greater probability than those with little experience (excess of security). According to other studies, however, the exact opposite occurs. The younger predictors tend to differentiate themselves from the masses because they don't have anything to lose, unlike the more experienced analysts that have more incentives to follow the "flock", because they do not want to ruin their reputation earned throughout the years. According to Tian J. et al. (2018), understanding forecast revisions is critical for weather forecast users to determine the optimal timing for their planning decisions.

All these factors highlight how irrational the process of forming expectations can be. It follows that each financial institution will have diametrically different expectations, as investment decisions and consequently the gains or losses will be based on proxies. These proxies will have as their object personal variables, intrinsic to each individual, such as the analyst's precision, risk appetite, social status, education, the role played within the credit institution, its reputation, the type of institution and its size and many other aspects that contribute to the analysis of expectations in the economic field and financial sector (a much discussed and constantly evolving sector). To this end, this work aims to break away from the patterns that characterize the analysis of traditional expectations, showing what could happen in a context as close as possible to reality, thanks to the use of a strongly non-standardized and irregular data set.

2.2 Sample and data description

We construct our sample using the forecasts of the euro-dollar exchange rate issued by several financial institutions, such as banks, research divisions of banks and research centres included in the Bloomberg platform. The data cover a period between the first quarter of 2007 and the second quarter of 2016. In these nine years a total of 120 predictors issued valid forecasts, from a minimum of 2 to a maximum of 929 individual forecasts. The total number of forecasts contained in our data set is 24,627, of which 16,572 are revisions of predictions existing for a future date. For each record (forecast) of the data set, it is possible to obtain the name of the predictor, the name of the country, state and continent in which the predictors have their headquarters; the classification for each predictor of the developing or developed economy; the date and the quarter on which the forecast was formulated; the classification of the type of forecasts: first forecast or revision of the forecast; the spot rate at the moment the forecast is presented and the spot rate on the date on which the revisions was made.

The dataset is organized as follows: for each quarter every single predictor was invited to submit forecasts on the exchange rate in euro-dollar currency for the end of the current quarter and the end of the following three quarters. The number of possible contributions was not limited, so any person could revise their estimates over the course of the quarter and present new forecasts as the end of the quarter approached. Furthermore, the forecasts are not presented simultaneously: a predictor can present its own on the first day of the quarter, and another predictor can present it at the end of the same quarter or on any other day in between. Due to the fact the predictors have no limits on the number of forecasts to be presented, and in the moment in which these forecasts have been expressed, the forecast horizon varies depending on the date on which each institution has decided to issue the forecast.

Therefore, our data set consists of time series with irregular spacing. In the vast majority of empirical literature, forecast data sets are organized in such a way that the frequency of projections is constant, i.e. equidistant projections, and this way of organizing the data has the advantage of allowing the use of standard tools of econometrics. In this way, all the information available in the analysis is preserved. Instead of eliminating forecasts that did not respect a specificity forecast horizon, we decided to examine how predictors revise their estimates in the path that leads to the date for which the forecast is made. In other words, we considered many forecasts, with a variable forecast horizon, issued for a common future date, instead of following the standard approach of considering only one forecast for a future date. In the time path leading to the terminal date for which the forecast was issued, the predictor's information set cannot decrease. It follows that, if the information set remains unchanged, the forecast should also remain unchanged, while if new information reaches the predictor, this information should be taken into account to review and improve or balance the forecasts issued previously. Therefore, the revisions should not worsen the forecasts. If the revisions improve the previously issued forecasts, this means that the new information has been incorporated in a complete and timely manner, and that the prices reflect all the available information. (Easterwood and Nutt, 1999).

2.3 Methodology: A descriptive approach to the analysis of forecasting revisions

The aim of this paragraph is to explain how the forecast error is determined, which arises as the difference, in absolute value, between the value of each individual forecast and/or revision and the corresponding spot rate recorded for the reference period. Every forecast and every revision are issued for a specific terminal date on a quarterly basis (31/03, 30/06, 30/09, 31/12). Predictors can decide whether to issue a revision of a forecast and a revision of a revision, or not. If they decide to issue it, we estimate the difference between the revision and the forecast (and, if necessary, between the revision and the revision). This difference, for each predictor, is classified as better, worse or equal revision. Therefore, using the forecast error, in absolute value, as a metric to evaluate the efficiency of the forecasts, we generated the following classification:

⇒ Revisions of non-variable forecasts: revisions of forecasts that have not changed compared to the previous forecast. For example, at time t the predictor presented a forecast of 1.31 and at time t + 1 it presented a new forecast with the same value of 1.31, compared to the same terminal date. In this case, the value of the forecast error does not change when you move between the two consecutive forecasts. Revisions that do not change the forecasts have been classified as equal revisions;

⇒ Variable forecast revisions: forecast revisions whose value has changed from the previous forecast. In this case, it is also possible to calculate whether the forecast error associated with the revision of the forecast is higher or lower than the error associated with the previous forecast. Therefore, we have divided these forecast revisions into the following two subsets:

- Revisions that improve forecasts: revisions of the forecasts that generate a forecast error less than the forecast error associated with the previous forecast. This revision conveys a forecast that converges towards the future real value of the variable;

- Revisions that worsen the forecasts: revisions of the forecasts that generate a forecast error that is greater than the forecast error associated with the previous forecast. This revision conveys a forecast that deviates from the future true natural value of the variable.

In theory, whenever predictors revise their forecasts, they should at least equalize the previous forecast issued, if not actually improve it, since it is assumed that in order to do so they are in possession of new information. But as we will see in the results section, this does not always happen. In fact, there is a percentage of worse forecasts, which even if lower than the better and equal revisions, shows that predictors are not always able to issue efficient forecasts. This mechanism can be generated by the inability to absorb new information completely and promptly, but also by the psychological factors to which we referred in the introductory session and in the first chapter of this dissertation, which influence the rationality of our choices.

2.4 Results and comment

The results achieved through the analysis of the Bloomberg dataset available, relating to the forecasts of exchange rates in euro-dollar currency, with a horizon from the first quarter of 2007 to the second quarter of 2016, were very satisfactory, as, in line with previous literature, they allow us to agree that predictors do not always make efficient predictions. This aspect, which we have already explored in the previous chapter, is caused by a plurality of factors, psychological and otherwise, which encourage predictors not to learn from their mistakes.

In a purely financial context, where exchange rate forecasts (as well as other variables strictly inherent to the sector) are certainly not achieved and issued by a single individual, but rather by offices made up of several ultra-qualified people, to speak of psychological paradigms of individuals, due to their personal beliefs and experiences, is quite limiting. In fact, in a context similar to the one we are talking about, which deals with the forecasts issued by banks among the largest in the world in terms of value of assets and equity, we must focus more on macroeconomic aspects, which can influence the efficiency of the forecasts issued by individual financial intermediaries as a whole.

Precisely for this reason, in the third and fourth chapters of this dissertation, two statistical tests are applied, which have the purpose of showing us if past forecasts influence future forecasts to the point of generating systematic errors., They also reveal if, among the 120 predictors analysed, there are one or more that act as market leaders, systematically preceding the forecasts issued by all the other predictors and generating such an influence that could generate the occurrence of a so-called "flock effect". This effect pushes banks to standardize their forecasts to those of one or more market leaders to limit the reputation effect, since, as well as for individuals, even for large financial and non-financial companies, the judgment of others is important to the point of pushing us to behave irrationally and very differently from our operating philosophy.

Below are the results obtained from the analysis of the historical series concerning the forecasts and revisions issued by the 120 financial institutions available in the Bloomberg dataset, in the horizon from the first quarter of 2007 to the second quarter of 2016. The initial situation, reported in Table 1, shows that the total of the forecasts and quarterly reviews is made up of 24,627 observations, of which 8,055 are the first forecasts. The other 16,572 represent the revisions of the first forecasts or other previous revisions. As widely explained in the previous paragraph, the revisions have been classified into better, equal and worse.

Table 1 - Initial situation

		Horizons			
Remark	1° Quarter	2° Quarter	3° Quarter	4° Quarter	Total
1° Prediction	1956	2067	2046	1986	8055
	41,63%	30,33%	30,58%	30,92%	32,71%
Better	818	1326	1075	914	4133
	17,41%	19,46%	16,07%	14,23%	16,78%
Equal	1569	2676	2771	2793	9809
	33,40%	39,27%	41,41%	43,48%	39,83%
Worse	355	745	799	731	2630
	7,56%	10,93%	11,94%	11,38%	10,68%
Total	4698	6814	6691	6424	24627
	100%	100%	100%	100%	100%

This Table describes the percentage of the forecasts and the revisions, and the sample size for each horizon, that characterize the dataset during the horizon considered, which runs from the first quarter of 2007 until the second quarter of 2016.

Reading Table 1, we can see how the higher percentage refers to equal revisions. This means that 39.83% of the times, the total revisions issued are the same as the previous forecasts, for the same terminal date. The table also shows the results achieved in the individual quarters, which demonstrate a growing trend in the long term, as a direct consequence of the volatility that the exchange rate forecasts have in the short term due to the fluctuations that characterize these types of markets. Another very important feature of our dataset is that. even if in a reduced percentage compared to the other two categories of revisions, we can see that in 10.68% of cases out of the total, the revisions worsen the forecasts previously issued. This is a symptom of the inability to absorb new information in the time path leading to the terminal date for which the revisions and forecasts have been issued. It should also be said that the trend of worse revisions tends to grow in the long term, a symptom of an increase in predictive inefficiency as we approach the terminal date for which the revisions were issued. Finally, as far as the better revisions are concerned, we find that in 16.78% of the cases, the revisions improve the forecasts previously issued. It should be noted, however, that unlike what should happen in a rational and efficient context, the trend of better revisions tends to decrease in the long term, a symptom of a reduction in the efficiency of the revisions issued.

Table 2 - Forecast Error Class

		Horizons			
Remark	1° Quarter	2° Quarter	3° Quarter	4° Quarter	Total
Better	818	1326	1075	914	4133
	29,83%	27,93%	23,14%	20,59%	24,94%
Equal	1569	2676	2771	2793	9809
	57,22%	56,37%	59,66%	62,93%	59,19%
Worse	355	745	799	731	2630
	12,95%	15,69%	17,20%	16,47%	15,87%
Total	2742	4747	4645	4438	16572
	100%	100%	100%	100%	100%

This Table describes the percentage revisions of the first prediction and the sample size of the different type of the revision that characterize the dataset during the horizon considered, which runs from the first quarter of 2007 until the second quarter

The percentages of revisions are shown in Table 2, without showing those relating to the first forecasts. This highlights a slight increase but not a change in the trend, which as reported in

Table 1 shows that the equal revisions are those with the highest percentage of the total, a symptom of a tendency to remain in the position in which we are at 59.19 %, without risking that a change could lead to a deterioration, as well as an improvement. The second percentage in order of magnitude is represented by better revisions with 24.94% of the total revisions, and which confirms, as in Table 1, the trend of a reduction in the efficiency of forecasts in the long term, but as we approach the terminal date for which the revisions have been issued.

Lastly, we find the worse revisions, which confirm that predictors are unable to absorb all the available information and exploit it to their advantage, as also in Table 2 we can see a growing trend in the long run. This means that predictors are not always able to improve their predictions. On the whole, 15.87% of the time, the revisions worsen the forecasts previously issued.

These first results suggest that both professional and non-professional investors exhibit behaviours that do not always tend to the traditional concept of rationality in the decision-making process. According to this concept, the expectations of economic agents with reference to an investment opportunity should be in line with the mathematical expectations based on the calculation of real probability, which aim to obtain the best possible outcome in terms of expected utility. To obtain these results it is necessary that the investment choices are always based on a complete series of information, in which the share price reflects at all times all the useful and necessary information in order to make the best possible choice on the market. This implies that there are no worse revisions, as the new information is readily available and usable by everyone.

Table 3 - Evidence of worsening revisions

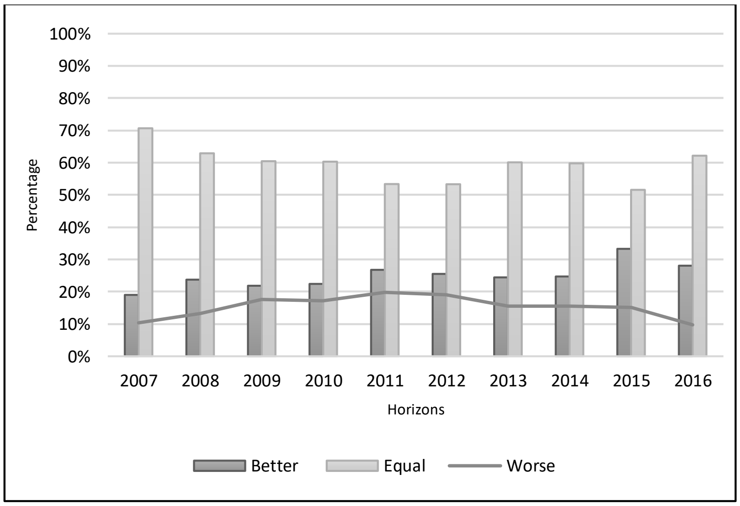
	Remark			
Horizons	Better	Equal	Worse	Total
2007	19,02%	70,68%	10,30%	100%
2008	23,75%	62,92%	13,33%	100%
2009	21,86%	60,47%	17,67%	100%
2010	22,43%	60,33%	17,24%	100%
2011	26,79%	53,39%	19,82%	100%
2012	25,53%	55,33%	19,15%	100%
2013	24,45%	60,12%	15,44%	100%
2014	24,73%	59,80%	15,47%	100%
2015	33,30%	51,59%	15,11%	100%
2016	28,08%	62,18%	9,74%	100%
2007-2016	24,94%	59,19%	15,87%	100%

This Table shows the revisions percentage of the first prediction divider for each year, that characterize the dataset during the horizon considered, which runs from the first quarter of 2007 until the second quarter of 2016.

As a further demonstration of the results achieved so far, in Table 3 we have reported the annual percentages of the equal, better and worse revisions, to show how the worse revisions have increased vigorously from 2007 to 2012, years that have been characterized by the speculative mortgage bubble subprime. This shows that in situations characterized by a high presence of uncertainty, even professional predictors cannot cope with price fluctuations, generating information asymmetries that undermine the pillars of the traditional economy, where individuals are always rational and systematically forecast efficient, as a direct consequence of the ability to absorb and use new information to one's advantage.

In 2009 the worst revisions increased by 4.34 percentage points and continued to grow until 2012 reaching 19.15%. On the contrary, the better revisions underwent a contraction in 2009, and then started to grow again in the following years, reaching 28.08% in 2016. The level of the worst revisions remained on average at the level reached in the central period of the crisis, showing a persistence uncertainty, to then begin a slow descent, which ended in 2016 thanks to the regulations and interventions of the respective Central Banks that have rebalanced the situation.

Figure 3 - Evidence of worse revision



Source: Author's own

This Figure shows the different trend that characterizes the better, worse and equal revisions of the first prediction during the horizon considered, which starts from the first quarter of 2007 until the second quarter of 2016. (Source: personal processing).

Furthermore, graphically in Figure 3 it is possible to note how the percentage of better revisions has always remained at an average constant level, which apparently seems to have been affected only in part by the negative effects of the financial crisis of subprime mortgages. Predictors have managed to absorb new information, limiting information asymmetries, and issuing efficient reviews. The occurrence of this trend occurred only partially, due to the presence of the worse revisions, which are constantly present in a smaller percentage, a symptom that not all financial intermediaries are able to be efficient.

Finally, to give further confirmation of the results achieved, in line with the existing literature (see Meese and Rogoff (1983), and more recently Beckmann and Czudaj (2017)), it was decided to compare whether the number of cases in which the error forecast obtained with a prediction based on a casual walk model is better in absolute terms than the forecast provided by a real professional forecaster.

The results shown in Table 4 show that the percentage of cases in which the forecast errors generated by the difference between the predictors forecasts for each period and the spot rate is higher than the forecast errors generated by the difference between the spot rate and the real value of the exchange rate generated at the end of each period, where:

⇒ A = abs (prediction - spot rate) < abs (sport rate – real value);

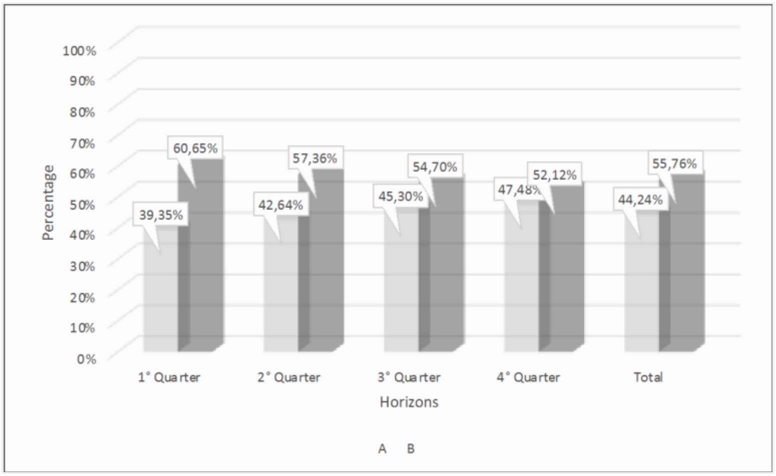
⇒ B = abs (prediction - spot rate) > abs (sport rate - real value);

Table 4 - Forecast Failure Rate

	Horizons				
RandomWalk	1° Quarter	2° Quarter	3° Quarter	4° Quarter	Total
A	1079	2024	2104	2125	7332
	39,35%	42,64%	45,3%	47,48%	44,24%
B	1663	2723	2541	2313	9240
	60,65%	57,36%	54,70%	52,12%	55,76%
Total	2742	4747	4645	4438	16572
	100%	100%	100%	100%	100%

This Table show that in each quarter considered the random walk model is more efficient than the forecasts issued by professional predictors.

Figure 4 - Evidence of Forecasts Failure Rate



Source: Author's own

This Figure shows that in each quarter the difference in absolute value between the forecast error issued by the predictors and the random walk model are always very pronounced. (Source: personal processing)

These results demonstrate that in each horizon considered, the random walk model is more efficient than the forecasts issued by a professional predictor in the sector. Therefore, in the specific case, the forecasts issued by the competent staff of the largest banks in the world by volume of assets and equity based on the ranking of 2007, the year of the beginning of our investigation, are less efficient in absolute terms. Furthermore, as shown in Figure 2, the difference in absolute value tends to decrease slightly in the long run, although to represent an efficient result it should be able to beat the random walk model.

In Appendix A.1 in descending order, the total number of worst revisions issued by each financial intermediary over the horizon from the first quarter 2007 to the second quarter 2016 has been reported.

2.5 Conclusion

The survey conducted on the forecasts of exchange rates in euro-dollar currency, from 2007 to the second quarter of 2016, showed that predictors would have performed better, that is to say, a forecast error in lower absolute value, using the random walk model or by issuing a forecast equal to the spot frequency known at the time of the forecast.

Therefore, based on the results achieved, it can be said that the reviews do not systematically improve the initial forecasts. Therefore, both in the short term, due to market volatility, and in the long term, due to the inability to fully and promptly absorb new information, predictors do not always prove efficient and rational in issuing their forecasts, in the path leading to the terminal date for which the forecast is issued (Kilian & Taylor, 2003).

To further verify the non-efficiency results achieved in this first chapter, it was decided to use the Hurst statistical test, to further measure whether the forecasts and revisions issued by the 120 financial institutions are efficient (H = 0.5). Furthermore, this statistical test will also allow us to measure the degree of influence that past forecasts issued by each predictor have on future forecasts, generating a redundant cycle of inefficient forecasts.

Appendix A. 1 - Number of worse forecasts issued by each predictor in the horizon considered.

List	Bank	Country	State	Worsening
1	Credit Suisse Group AG	Zurich	Switzerland	134
2	Barclays	London	United Kingdom	114
3	Skandinaviska Enskilda Banken	Howald	Luxembourg	104
4	Westpac Banking	Sydney	Australia	86
5	Wells Fargo	Sioux Falls	United States	82
6	Commerzbank	Frankfurt am Main	Germany	78
7	Mitsubishi UFJ Financial Group	Tokyo	Japan	70
8	Danske Bank	Copenhagen	Denmark	70
9	Monex Europe Ltd	London	United Kingdom	70
10	Canadian Imperial Bank of Commerce	Toronto	Canada	56
11	Royal Bank of Scotland	Edinburgh	United Kingdom	56
12	Rabobank	Utrecht	Netherlands	54
13	Scotiabank	Toronto	Canada	53
14	Bank of America Corporation	Charlotte	United States	51
15	X-Trade Brokers Dom Maklerski	Warsaw	Poland	51
16	BNP Paribas	Paris	France	48
17	Citigroup	New York	United States	48
18	Banco Bilbao Vizcaya Argentaria	Bilbao	Spain	45
19	National Bank Financial	Montreal	Canada	45
20	Commonwealth Bank of Australia	Sydney	Australia	44
21	Sumitomo Mitsui Trust Bank	Tokyo	Japan	43
22	National Australian Bank Limited	Melbourne	Australia	40
23	Alpha Bank AE	Athens	Greece	39
24	Oversea-Chinese Banking Corp	Taipei	Taiwan	39
25	Standard Chartered	London	United Kingdom	39
26	Aletti Gestielle SGR	Milan	Italy	37
27	UniCredit	Milan	Italy	35
28	HSBC Holdings	London	United Kingdom	34
29	CIB Bank	Budapest	Hungary	33
30	JPMorgan Chase	New York	United States	31
31	DZ Bank	Frankfurt	Germany	30
32	Morgan Stanley	New York	United States	30
33	SJS Markets Limited	Hong Kong	China	28
34	ING Financial Markets	New York	United States	28
35	Societe Generale	Paris	France	28
36	Australia & New Zealand Banking Group	St Docklands	Australia	27
37	Lloyds Bank Commercial Banking	London	United Kingdom	27
38	Dresdner Bank AG	Frankfurt am Main	Germany	26
39	RBC Capital Markets	New York	United States	26
40	Saxo Bank	Hellerup	Denmark	26
41	Silicon Valley Bank	Santa Clara	United States	26
42	Landesbank Baden-Wuerttemberg	Stuttgart	Germany	25
43	Standard Bank Group	Lilongwe	Malawi	25
44	Erste Group Bank	Vienna	Austria	24
45	Swedbank	Sundbyberg	Sweden	23
46	Nordea Bank	Nordea	Finland	22
47	BMO Capital Markets	Toronto	Canada	21
48	Credit Agricole CIB	Paris	France	21
49	TD Securities	Toronto	Canada	21
50	TMS Brokers	Warsaw	Poland	20
51	DNB Bank ASA	Oslo	Norway	19
52	Petrocommerce Bank	Moscow	Russian Federation	19
53	Argentex LLP	London	United Kingdom	14
54	Investec	London	United Kingdom	14
55	HDFC Bank LTD	Mumbai	India	13
56	Intesa Sanpaolo	Turin	Italy	13

57	Nomura Bank International	London	United Kingdom	13
58	Vadilal Forex	Ahmedabad	India	13
59	Ceskoslovenska Obchodni Banka	Prague	Czech Republic	12
60	Emirates NBD PJSC	Dubai	United Arab Emirates	12
61	Macquarie Bank	Sydney	Australia	12
62	Mouvement Desjardins	Levis	Canada	12
63	UBS AG	Zurich	Switzerland	12
64	Prestige Economics LLC	Austin	United States	11
65	Swissquote Bank	Zurich	Switzerland	11
66	Banca Aletti & C spa	Milan	Italy	10
67	Norddeutsche Landesbank	Hanover	Germany	10
68	Redtower	San Francisco	United States	10
69	Bank of New Zealand	Auckland	New Zealand	9
70	Deutsche Bank	Frankfurt am Main	Germany	9
71	Banca Monte dei Paschi di Siena S.p.A.	Siena	Italy	9
72	Rand Merchant Bank	Sandton	South Africa	9
73	ABB Ltd	Zurich	Switzerland	8
74	Ebury Partners UK Ltd	London	United Kingdom	8
75	Ageas Finance NV	Utrech	Netherlands	8
76	Casa De Bolsa Ve Por Mas SA de CV	Mexico City	Mexico	8
77	Brown Brothers Harriman	New York	United States	7
78	Hamilton Court FX LLP	London	United Kingdom	7
79	Mecklai Financial Services	Mumbai	India	7
80	LCA Consultores	Sao Paulo	Brazil	6
81	Malayan Banking Berhad	Kuala Lumpur	Malaysia	6
82	Natixis	Paris	France	6
83	Alpha Bank London Ltd	London	United Kingdom	4
84	Cinkciarz.pl	Lubusz	Poland	4
85	4CAST	London	United Kingdom	4
86	Lehman Brothers Inc.	New York	United States	4
87	B. Metzler seel. Sohn & Co.	Frankfurt	Germany	4
88	Paradigm Wealth Management	Bridgewater	United States	4
89	Alior Bank Spolka Akcyjna	Warsaw	Poland	3
90	DAY Bank	Tehran	Iran	3
91	HIFX PLC	Berkshire	United Kingdom	3
92	ICICI Bank	Mumbai	India	3
93	Investment Capital Ukraine	Kiev	Ukraine	3
94	Banco Santander	Madrid	Spain	3
95	St George Bank	Sydney	Australia	3
96	Bayerische Landesbank	München	Germany	2
97	Dom Maklerski AFS Sp zoo	Warsaw	Poland	2
98	Goldman Sachs Group	New York	United States	2
99	IDEAglobal	Singapore	Singapore	2
100	Bank Pekao SA	Warsaw	Poland	2
101	Validus Risk Management	Eton	United Kingdom	2
102	Advanced Currency Markets	Geneva	Switzerland	1
103	AFEX	Woodland Hills	United States	1
104	Bank of New York Mellon	New York	United States	1
105	CIMB Group	Kuala Lumpur	Malaysia	0
106	HBOS	Halifax	United Kingdom	0
107	KBC Groep	Brussels	Belgium	0
108	Laurentian Bank of Canada	Montreal	Germany	0
109	MIG Investments	Chelmsford	United Kingdom	0
110	Raiffeisen	Vienna	Austria	0
111	Renaissance Capital Holdings	Hamilton	Bermuda	0
112	RHB OSK Securities	Bangkok	Thailand	0
113	VTB Capital	London	United Kingdom	0
114	Yes Bank	Mumbai	India	0

This Table shows the ranking of predictors, based on the number of worsening revisions issued in descending order, over the horizon considered, ranging from the first quarter of 2007 to the second quarter of 2016. The number of banks reported is 114 out of 120, because for six predictors there are no revisions training.

Appendix A. 2 - List of banks used in the dataset

Sigle	Specialisation	Bank_name	Continent
ABA	Commercial bank	Alpha Bank AE	Europe
ABB	Financial Services	ABB Ltd	Europe
ACM	Financial Services	Advanced Currency Markets	Europe
AFE	Financial Services	AFEX	America
AFX	Commercial bank	Alpha Bank London Limited	Europe
AGS	Financial Services	Aletti Gestielle SGR	Europe
ALI	Commercial bank	Alior Bank Spolka Akcyjna	Europe
ANZ	Commercial bank	New Zealand Banking Group	Oceania
ARG	Financial Services	Argentex LLP	Europe
BAA	Commercial bank	Banca Aletti C. spa	Europe
BAR	Bank holding	Barclays	Europe
BAY	Governmental credit institution	Bayerische Landesbank	Europe
BBH	Investment bank	Brown Brothers Harriman	America
BMO	Commercial bank	Bank Of Montreal	America
BNP	Commercial bank	BNP Paribas	Europe
BNY	Commercial bank	Bank of New York Mellon	America
BNZ	Commercial bank	Bank of New Zealand	Oceania
BOA	Commercial bank	Bank of America Corporation	America
BTM	Commercial bank	Mitsubishi UFJ Financial Group, Inc.	Asia
BVA	Commercial bank	Banco Bilbao Vizcaya Argentaria	Europe
CAG	Bank holding	Credit Agricole CIB	Europe
CBA	Commercial bank	Commonwealth Bank of Australia	Oceania
CBH	Commercial bank	CIB Bank	Europe
CCZ	Financial Services	Cinkciarz.pl	Europe
CFC	Financial Services	SJS Markets Limited	Asia
CIB	Commercial bank	Canadian Imperial Bank of Commerce	America
CIT	Bank holding	Citigroup	America
CMB	Bank holding	CIMB Group	Asia
COB	Commercial bank	Ceskoslovenska Obchodni Banka	Europe
COM	Commercial bank	Commerzbank	Europe
CRB	Commercial bank	Credit Europe Bank	Europe
CST	Financial Services	4CAST	Europe
CSU	Bank holding	Credit Suisse Group AG	Europe
DB	Commercial bank	Deutsche Bank	Europe
DBD	Islamic bank	DAY Bank	Asia
DBF	Commercial bank	Dresdner Bank AG	Europe
DMS	Financial Services	Dom Maklerski AFS Sp zoo	Europe
DNB	Commercial bank	DNB Bank ASA	Europe
DNS	Commercial bank	Danske Bank	Europe
DZB	Cooperative bank	DZ Bank	Europe
EMI	Commercial bank	Emirates NBD PJSC	Asia
EPT	Financial Services	Ebury Partners UK Ltd	Europe
ERT	Bank holding	Erste Group Bank	Europe
FRT	Finance company	Ageas Finance NV	Europe
FXP	Financial Services	FXPRIMUS Ltd	Africa
GS	Bank holding	Goldman Sachs Group	America
HBS	Bank holding	HBOS	Europe
HDF	Commercial bank	HDFC Bank LTD	Asia
HIF	Financial Services	HIFX Plc	Europe
HMC	Financial Services	Hamilton Court FX LLP	Europe

HMC	Financial Services	Hamilton Court FX LLP	Europe
HSB	Bank holding	HSBC Holdings	Europe
I1	Commercial bank	Investec	Europe
ICI	Commercial bank	ICICI Bank	Asia
ICU	Financial Services	Investment Capital Ukraine	Europe
IDE	Financial Services	IDEAglobal	Asia
ING	Investment bank	ING Financial Markets	America
ISP	Commercial bank	Intesa Sanpaolo	Europe
JPM	Bank holding	JPMorgan Chase	America
KBC	Bank holding	KBC Groep	Europe
LBB	Governmental credit institution	Landesbank Baden-Wuerttemberg	Europe
LBC	Commercial bank	Laurentian Bank of Canada	Europe
LCA	Financial Services	LCA Consultores	America
LEH	Investment bank	Lehman Brothers Inc.	America
LLY	Commercial bank	Lloyds Bank Commercial Banking	Europe
M2M	Commercial bank	M2M Private Bank	Europe
MAY	Commercial bank	Malayan Banking Berhad - MAYBANK	Asia
MB	Investment bank	Macquarie Bank	Oceania
MCK	Financial Services	Mecklai Financial Services	Asia
MDE	Commercial bank	Mouvement Desjardins	America
MET	Bank holding	B. Metzler seel. Sohn & Co.	Europe
MIG	Financial Services	MIG Investments	Europe
MPS	Commercial bank	Banca Monte dei Paschi di Siena S.p.A.	Europe
MS	Commercial bank	Morgan Stanley	America
NAB	Commercial bank	National Australian Bank Limited	Oceania
NBF	Commercial bank	National Bank Financial	America
NDA	Commercial bank	Nordea Bank	Europe
NMR	Investment bank	Nomura Bank International	Europe
NRD	Governmental credit institution	Norddeutsche Landesbank	Europe
NTX	Commercial bank	Natixis	Europe
OCB	Commercial bank	Oversea-Chinese Banking Corp	Asia
PBR	Commercial bank	Piraeus Bank Romania SA	Europe
PEK	Commercial bank	Bank Pekao SA	Europe
PET	Commercial bank	Petrocommerce Bank	Europe
PRT	Financial Services	Prestige Economics LLC	America
PWM	Financial Services	Paradigm Wealth Management	America
RAB	Cooperative bank	Rabobank	Europe
RAF	Commercial bank	Raiffeisen	Europe
RBC	Investment bank	RBC Capital Markets	America
RBS	Bank holding	Royal Bank of Scotland	Europe
RED	Financial Services	Redtower	America
REN	Bank holding	Renaissance Capital Holdings	America
RHO	Financial Services	RHB OSK Securities	Asia
RMB	Investment bank	Rand Merchant Bank	Africa
SAN	Commercial bank	Banco Santander	Europe
SAX	Securities firm	Saxo Bank	Europe
SCB	Bank holding	Standard Chartered	Europe
SCI	Commercial bank	Scotiabank	America
SEB	Commercial bank	Skandinaviska Enskilda Banken	Europe
SG	Commercial bank	Societe Generale	Europe
SGB	Commercial bank	St George Bank	Oceania

STA	Financial Services	Monex Europe Ltd	Europe
STB	Bank holding	Standard Bank Group	Africa
SUM	Commercial bank	Sumitomo Mitsui Trust Bank	Asia
SVB	Commercial bank	Silicon Valley Bank	America
SWE	Savings bank	Swedbank	Europe
SWQ	Commercial bank	Swissquote Bank	Europe
TDS	Investment bank	TD Securities	America
TMS	Financial Services	TMS Brokers	Europe
UBS	Commercial bank	UBS AG	Europe
UCM	Commercial bank	UniCredit	Europe
UFS	Financial Services	UFS Finance Investment Company	Europe
VDE	Financial Services	Vadilal Forex	Asia
VPM	Commercial bank	Casa De Bolsa Ve Por Mas SA de CV	America
VRM	Financial Services	Validus Risk Management	Europe
VTC	Commercial bank	VTB Capital	Europe
WF	Bank holding	Wells Fargo	America
WLB	Investment & trust corporation	WestLB	Europe
WPC	Commercial bank	Westpac Banking	Oceania
XTB	Financial Services	X-Trade Brokers Dom Maklerski	Europe
YES	Commercial bank	Yes Bank	Asia

This table shows the name of the financial institutions used in this dissertation and the abbreviation with which they are listed on the Bloomberg platform, from which the relevant time series and the specialization that qualifies the type of activity carried out by the financial institution have been downloaded.

CHAPTER III

Do predictors behave efficiently? Analysis of the historical series

3.1 Literature Review and hypotheses development

The creation of this statistical coefficient is due to Harold Edwin Hurst, a British hydrologist who developed this index in the early twentieth century to keep the Nile River basin under control. His goal was to monitor the water level, ensuring that the quantity present was never too much or too little. The problem was linked to the fact that the water level in any water basin is closely related to the amount of rainfall, an event that follows a "Random Walk" trend. For this reason, the hydrologist developed a statistical tool known as "Hurst exponent (H)", capable of distinguishing a random series from a non-random one even if the random series is not normally distributed. Initially he measured the fluctuations of the water level around its average value in a given period of time but obtained a result strictly proportional to the horizon. For this reason, Hurst decided to create a dimensionless index, standardizing the measurement, dividing the interval by the standard deviation of the observations, hence the name "rescaled interval analysis (R / S analysis)". This statistical process, known as fractional Brownian motion, implies the presence of long-term dependence in the observations. A fractional Brownian motion can have normally distributed increments, but not independent of a pure Brownian motion.

Over the years, the Brownian motion has become a very important tool in the field of probability theory, through which a plurality of phenomena have been described, such as the prices of financial securities, the diffusion of heat, animal populations and bacteria, an illness, sound or light. The origin of the name Brownian is due to the Scottish botanist Robert Brown, who in 1827 observed how pollen particles suspended in water moved continuously in a random and unpredictable way. These results were taken up by Einstein in 1905, who demonstrated how the movement of the particles could be described through algebraic formulas, assuming that the jumps of these masses were due to the random collisions of the pollen particles with the water molecules.

Further studies on the Brownian motion were conducted by Bachelier, who, in his article entitled "Theorie de la speculation", was the first to demonstrate the possibility of using advanced mathematics in finance. His study assumed that the markets were able to eliminate financial risk: investors prepare forecasts on future movements of securities on the assumption that in an ideal market the change in prices today is not influenced by the change in prices recorded in the past, denoting a character of independence. Basically, he hypothesized that the sudden fluctuations of the securities were due to irrational factors intrinsic to the markets in which these financial instruments were traded. At the basis of this study was the idea that investors were rational, but as increasingly demonstrated in the financial sphere, it is not only the market that is irrational, but above all the individuals who operate there. This is the reason why the theory of efficiency of the classical school has been repeatedly criticized by mathematicians and economists, such as Mandelbrot (1968) and Peters (1991-1994), according to whom there are no homogeneous investors, equal to each other in the selection of titles and information. There are several types of investors who show how the financial market is chaotic and imperfect overall.

According to Mandelbrot et al. (1968), unlike classical theory, the distribution of equity returns is not accidental, otherwise events such as the crisis of 1929, the collapse of the Wall Street stock exchange in 1987 and the great recession of 2007 would have occurred thousands of years later. The author claimed that price fluctuations are not independent or Brownian but are rather influenced by past events. To demonstrate this, he used Hurst's statistical test to investigate whether a trend can be identified in time series or if their trend follows a random path, as speculated by the efficient market theory introduced by Eugene Fama in the 1970s, according to which the market is efficient, when the price of an asset reflects all the available information. According to this definition the price must be a martingale, since the conditional expectation on t + 1 is equal to the price of the stock at the moment t. The hypothesis behind this theory requires that stock prices fully and promptly reflect new information.

In mathematics, trend detection took the form of a time series autocorrelation search. Much of the literature has developed from Hurst's work on river flows, such as the extension of the scaled analysis by Anis and Lloyd (1963), Mandelbrot et al. (1969). Others, such as Peters (1991-1994), applied the Hurst index to financial time series analysis, introducing the fractal market hypothesis (FMH), a theory based on the assumption that returns are not a priori "log-normal" and "unrelated", generating a plurality of more diversified return behaviours.

Subsequently, Lipka and Los (2002) also measured the persistence of the daily returns of eight European equity indices, discovering that the Hurst exponent allows one to measure correctly the long-term dependence of data sets. The authors also demonstrated that FTSE returns represent an ultra-efficient market with an abnormally rapid "average reversal" compared to that possible with a Brownian Geometric Motion. In the same year, Corazza and Malliaris (2002) also studied the returns of the various currency markets, noting that the value of the Hurst exponent is statistically different from the 0.5 in most samples. Many studies in the field of eco-physics have also examined the properties and phenomena of financial time series through interdisciplinary studies and have found significant deviations from random walking and the presence of long memory in time series. These include Cajueiro and Tabak (2004), who studied long-term dependency and efficiency in stock indices for 11 emerging markets together with the United States and Japan. To do this, they adopted a "rolling sample" approach and calculated the median exponents of Hurst to evaluate the relative efficiency of these stock markets. Their results have shown that Asian stock markets are more inefficient than Latin American ones and that developed markets are in first place in terms of efficiency.

Other studies, such as those of Kyaw et al. (2006), analysed the degree of long-term dependence of the Latin American financial markets, measuring the mono-fractal Hurst exponent (MRA) of the equity and currency markets of Latin America. They found that non-employee financial return rates are normal, non-stationary, non-ergodic and long-term. In addition, Singh & Prabakaran (2008) examined the performance spectrum of Indian stock markets using various statistical tests for data normality. The flow analyses were rescaled, and the Hurst exponent evaluated. They concluded that Indian capital markets are not random and therefore do not form a population that is normally distributed. In addition, the Brownian geometric movement cannot accurately model stock prices due to significant memory effects.

Alvarez-Ramirez et al. (2008), analysed the dynamic behaviour of the US stock markets through the time variations of the Hurst exponent, estimated with a reduced fluctuation analysis (DFA) on the moving windows of daily indices, for the Dow Jones time series, from 1928 to 2007, and for S&P 500, from 1950 to 2007. The results of the analysis showed an irregular trend in the Hurst exponent, where episodes of persistent low and high alternate.

In addition, Yuan et al (2009), analysed the daily returns of the Shanghai stock price index using the DFA method and found that there are two different types of time series multi-fractality sources, and nonlinear temporal correlations. It was found that when the share price index rises and falls drastically, a strong variability is clearly characterized by the generalized exponents of Hurst. They used measures based on Hurst's generalized exponents to compare market financial risks.

And yet, Yue et al (2010), used the method of analysis of the deducted fluctuations (DFA) to detect the long-range correlation and scale properties of Beijing's daily rainfall series from 1973 to 2004 before and after the addition of different trends to the original series. However, we were unable to find studies that have empirically detected a direct relationship between the Hurst exponent and the predictability of security prices. The DFA (Fluctuation Analysis) technique (Detrended Fluctuation Analysis) was introduced to investigate the correlations between law and long-range power between DNA sequences by Peng et al. (1992) and Stanley et al. (1992). In the method, the entire data sequence was divided into a number of smaller non-overlapping cells, each containing an equal number of data points. The method was found to be an efficient method for accurately calculating the Hurst exponent.

Mitra (2012), using the daily values of twelve series of stock indexes, estimated the Hurst exponent, noting that the value of the index of the complete series revolves around 0.50 to confirm the efficiency of the market. Capital market theories are based on the assumption that security prices are martingale, which implies that the expected value of the security price is the same as the price in the previous period. Therefore, security prices follow random paths and the returns on financial securities are unpredictable. Furthermore, the author has also shown that the coefficient value varies considerably when the time series is divided into a smaller series, showing profitable trading opportunities in the periods in which the exponent reaches high values.

Ohers, such as Rejichi et al. (2012), tested the evolutionary efficiency on the main stock markets of the Middle East and North Africa (MENA), using the empirical approach based on the Hurst exponent, using a mobile sample with a 4-year time window. The results of the analysis conducted on a sample covering a daily frequency ranging from January 1997 to December 2007, show that all returns on MENA stocks have a long-term memory and some markets are becoming more efficient.

Sensoy (2013), studied the variable efficiency over time of 15 stock markets in the Middle East and North Africa (MENA), through the analysis of the generalized Hurst exponent approach, of daily data with a floating window technique. The study spanned six years, from January 2007 to December 2012. The results reveal that all the stock markets in the Middle East and North Africa analysed have varying degrees of long-term dependency.

Lahmiri (2015), investigated the long-range dependency for twelve international stock markets before, during and after the 2008 financial crisis, through the analysis of the deducted fluctuation (DFA) and the scale analysis (R / S)., This allowed us to estimate the Hurst exponent for each of the variational modes obtained with variable-mode decomposition (VMD), a technique that allows the decomposition of stock market data into a finite set of modes, which show long-term trends and short-term movements of stock market data. The results of this study showed persistence in long-term trends, while short-term variations are anti-persistent before, during and after the 2008 financial crisis.

Kulish et al. (2016), have investigated the use of the Hurst coefficient to classify time series of financial data that have different periods. The results of this article show that historical series with large H-index values can be predicted with greater precision than those with H values close to 0.5. Therefore, the bigger the H value, the stronger the trend. It follows that it can be said that the exponent of Hurst provides a good measure of predictability.

The application of the Hurst coefficient to the historical series available has made it possible to obtain a double result. On the one hand, the index was used to demonstrate that the predictions issued by the predictors are not efficient (H other than 0.5). The results as stated by Mandelbrot et al. (1969), show that predictors have behaviours that do not tend to the traditional concept of rationality, since their economic expectations are not always in line with mathematical expectations based on real probabilistic calculations, which aim to obtain the maximum possible satisfaction.

On the other hand, the second result obtained by calculating the Hurst coefficient, allowed us to demonstrate that the forecasts issued in the past by the financial institutions studied have an influence on future forecasts. This allows us to say that if predictors are wrong in the past, they will also be wrong in the future, continuing to be inefficient. This concept is in fact linked to the inability of the predictors to improve their forecasts due to the new information that is gradually made available in the path leading to the terminal date for which the forecast is made.

Sukpitak et al. (2016), analysed the evolution of the Hurst exponent of the SET index over time, as a measure of market efficiency, through the DFA method. The results showed that the Hurst index tends to be 0.5 (efficient market), confirming that emerging markets are becoming more efficient. In addition, they also studied the development of the Hurst statistical coefficient, in the period from 2006 to 2015 of the SET index compared to the MAI index, discovering that the deviation of Hurst from the market efficiency value of 0.5 per the MAI index is greater than that of the SET index. This made it clear to the authors that SET is more efficient than MAI.

Jin (2016) analysed the dynamics of the Hurst exponent of the returns of the Asian stock markets in the context of the financial crisis of 2008. The results they achieved show that the returns are characterized by the presence of long memory in the period of the financial crisis of 2008, symptom that the 2008 financial crisis negatively affected the efficiency of the Asian stock markets.

Bariviera et al. (2017), test the presence of long memory in the transaction time series from a Bitcoin platform, from 2011 to 2017, calculating the Hurst exponent using the differentiated fluctuation analysis method, using a sliding window to measure long dependence radius. The results of their analysis show that the values of the Hurst exponent change significantly during the first years of Bitcoin's existence, tending to stabilize in recent times.

Wei (2018), examined the liquidity of 456 different cryptocurrencies, showing that the predictability of the yield decreases with increasing market liquidity. Therefore, the results achieved by the author show that there is a strong relationship between the Hurst exponent and liquidity, which allows him to say that liquidity plays a significant role in market efficiency and in the predictability of new cryptocurrencies.

Yang et al. (2019), used the index to measure the efficiency of the exchange rate of the Euro against the Swiss franc (EUR / CHF) from 2002 to 2017. The results showed that the level of long-term returns, measured with the values of the Hurst coefficient, stood at an efficiency level of 0.5, while as regards the infra-daily yield indices on the EUR / CHF exchange rate market, most of the values of the Hurst index evaluates the anti-persistence values ($H < 0.5$) which are a symptom of the inefficiency of the intra-daily market.

Mnif et al. (2019), analyse the efficiency of the Islamic market and Sukuk and focus on the presence of investor herding behaviour (HB) captured by the estimate of the Hurst exponent. The results show that, in the first place, there is a strong correlation between the prices and returns of the Islamic market and Sukuk. Secondly, using Hurst's robust estimate, it is noted that "DJIM" is the most efficient market. The results of the Hurst exponent's estimate show that HB is more intense in the Islamic stock market. These results also indicate the nonexistence of this behaviour in the studied market of Sukuk.

Milos et al. (2020), analysed seven stock markets in Central and Eastern Europe (EEC) through the Hurst index, using recent financial data up to August 2018. The results achieved show that the returns of the stock indices show long-term correlations, supporting the idea that the equity markets in question are not efficient markets and have not reached a mature stage of market development.

We innovate existing literature, using a data set of the Bloomberg platform, never analysed before, which deals with the forecast of the exchange rates in euro-dollar currency issued by the main world banks. The idea of our analysis is to verify whether the bank historical series are efficient ($H = 0.5$) or inefficient. If the analysed series prove to be inefficient, we will begin to measure the degree of persistence ($H > 0.5$) or anti-persistence ($H < 0.5$) which characterizes the trend of each variable analysed. Furthermore, using the idea used by Sukpitak et al. (2016), it was decided to measure the average deviation of the forecasts issued by the individual banks with respect to the efficiency value of the known Hurst index. Secondly, the same operation was also carried out for the average forecasts issued by the banks grouped by continent. The calculated difference will allow us to identify first which single bank and then which continent have average forecasts closer to the efficiency threshold.

3.2 Methodology

The mathematical procedure which led to the estimate of the Hurst coefficient for the forecasts issued by each financial institution of the Bloomberg dataset that we are analysing, took place in the following way:

- We calculated the cumulative deviation of the observations from their average, during one of the two time periods (N) explained above for each time series of interest:

$$Xt,n = S;\ t\ (et - MN)\ \ (1)$$

where:

  - $Xt,n \rightarrow$ is the cumulative deviation of the period N;
  - $et \rightarrow$ is the observation t;
  - $MN \rightarrow$ is the average of the observations and t in the period N.

- Then we calculated the range of this cumulative distribution as the difference between the maximum value and the minimum value it took:

$$RN = MAX(Xt,n) - MIN(Xt,n)\ \ (2)$$

- Finally, we divided the range (RN) by the standard deviation (S) of the observations (et) in the period N in order to standardize the measurement. Furthermore, Hurst found that $R\ /\ S$ could be estimated by using the following equation:

$$RN/S = (a * N) * H\ \ (3)$$

where:

- H → is the exponent of Hurst;
- a → is a constant;
- RN/S → is the rescaled range.

- Furthermore, passing to logarithms, we have that:

$$log(R/S) = H * log(N) + log(a) \quad (4)$$

where:

- H can be estimated by regressing the $log(R/S)$ against the $log(N)$.

There are three classes of relevant values of the Hurst exponent:

- If $H = 0.5$ → the analysed series follows a random walk process, which means that the range grows with the square root of time and there is no long-term statistical dependence. The historical series analysed are unrelated and it follows that the present does not affect the future. The underlying probability distribution may be the normal one, but it may not be so since the R / S analysis manages to identify a random series regardless of the underlying distribution type;

- If $0 < H < 0.5$ → we have a system in which if for example the last observation is "up" it is likely that the subsequent movement is "down" and vice versa. The strength of this "anti-persistence" in the series is greater the closer H is to zero;

- If $0.5 < H < 1 \rightarrow$ the analysed series shows a "persistent" behaviour. This means that if the trend of the historical series has been positive in the last period, it is likely to be positive also in the following period and vice versa. The level of this persistence is greater the closer H is to the value of 1. Therefore, the historical series is characterized by the presence of trends that persist over time. The trend of a six-month period influences the behaviour in the subsequent six-month periods, as well as a ten-year period which influences the other ten-year periods and so on.

Based on the class into which the different variables analysed through the Hurst test converge, we are able to measure the degree of correlation that exists between past and future forecasts, showing how much our past influences our future. In fact, the problem lies in the fact that as much as you want to try to learn from your mistakes and avoid repeating them in the future, it is difficult not to run into errors of judgment.

We are always influenced by the psychological stereotypes underlying our beliefs and culture, which we tend to use to speed up and simplify the process that leads to the formulation of our choices in the economic and financial field. This allows us to say that predictors, professional or non-professional, will always tend to manifest irrational behaviour, which violates the classical theory underlying the concept of efficiency.

3.3 Main results[10]

The results obtained through the application of the Hurst test to the available historical series, show that investors, both professional and non-professional, are not efficient. The coefficient, calculated for all the financial institutions available, shows that the forecasts and revisions issued are not in line with the mathematical expectations based on the calculation of the probabilities, which aims to achieve the greatest possible satisfaction. However, it must be said that there is a predictor that has a value of H = 0.5, but which, due to the limited sample size, cannot be considered reliable (see Appendix A.3).

We specifically report the results for each individual bank, on each continent.

In Table 5, among the banks of the oceanic continent analysed, the National Australian Bank Limited and Westpac Banking (H = 0.81) have the highest persistence value, while St George Bank is the one with the lowest index of the entire continent (H = 0.65).

Table 5 - Coefficient of Hurst Banks Oceania

Bank	Specialisation	Sample size	Coefficient	Continent
National Australian Bank Limited	Commercial bank	561	0,81	Oceania
Westpac Banking	Commercial bank	463	0,81	Oceania
Macquarie Bank	Investment bank	86	0,80	Oceania
Commonwealth Bank of Australia	Commercial bank	477	0,78	Oceania
Australia & New Zealand Banking Group	Commercial bank	318	0,74	Oceania
Bank of New Zealand	Commercial bank	146	0,73	Oceania
St George Bank	Commercial bank	37	0,65	Oceania

This Table shows the Hurst coefficients calculated for each financial institution in the oceanic continent and the sample size of the forecast on which the statistical test was applied. Highlighted in red, we report the financial institution with the highest value of the calculated index.

[10] For a detailed description of the dataset used in the analysis of chapter 2, please see par. 1.2.

In Table 6 the measurement of the Hurst index was applied to only three units, the African continent being the one with the least number of banks available in the dataset. The results show that there are no financial institutions with an index value of H = 0.5, so even in this case we can say that the forecasts and revisions issued by the predictors are not efficient. Furthermore, the bank with the highest coefficient is the Rand Merchant Bank (H = 0.80), while FXPRIMUS Ltd (H = 0.10) is anti-persistent, although it must be said that the small sample size makes the result unreliable for analysis purposes.

Table 6 - Coefficient of Hurst Banks Africa

Bank	Specialisation	Sample size	Coefficient	Continent
Rand Merchant Bank	Investment bank	56	0,80	Africa
Standard Bank Group	Bank holding	179	0,76	Africa
FXPRIMUS Ltd	Financial Services	3	0,10	Africa

This Table shows the Hurst coefficients calculated for each financial institution in the African continent and the sample size of the forecast on which the statistical test was applied. Highlighted in red, we report the financial institution with the highest value of the calculated index.

The results shown in Table 7 show that the financial institutions of the Asian continent, as well as those of the Oceanic and African continent do not have values of the index of H = 0.5. It follows that once again we can say that the euro-dollar exchange rate market, unlike what Fama et al. (1960) is not efficient, since predictors are not rational, and the forecasts provided do not readily reflect all available information. Furthermore, all the banks of the continent in question have persistence values (H> 0.5) that allow us to affirm the presence of long-term memory. The bank with the highest persistence index on the entire continent is Malayan Banking Berhad - May Bank (H = 0.82).

Table 7 - Coefficient of Hurst Banks Asia

Bank	Specialisation	Sample size	Coefficient	Continent
Malayan Banking Berhad - MAY Bank	Commercial bank	128	0,82	Asia
Oversea-Chinese Banking Corp	Commercial bank	193	0,80	Asia
DAY Bank	Islamic bank	59	0,79	Asia
Emirates NBD PJSC	Commercial bank	105	0,77	Asia
Vadilal Forex	Financial Services	175	0,77	Asia
MUFG	Commercial bank	351	0,77	Asia
RHB OSK Securities	Financial Services	26	0,76	Asia
HDFC Bank LTD	Commercial bank	79	0,76	Asia
CIMB Group	Bank holding	22	0,73	Asia
Sumitomo Mitsui Trust Bank	Commercial bank	279	0,73	Asia
ICICI Bank	Commercial bank	65	0,73	Asia
SJS Markets Limited	Financial Services	130	0,71	Asia
IDEAglobal	Financial Services	19	0,64	Asia
Mecklai Financial Services	Financial Services	48	0,60	Asia
Yes Bank	Commercial bank	11	0,60	Asia

This Table shows the Hurst coefficients calculated for each financial institution on the Asian continent and the sample size of the forecast on which the statistical test was applied. Highlighted in red, we report the financial institution with the highest value of the calculated index.

Table 8 shows the estimated values of the Hurst coefficient for the American continent, for which, as well as for the others analysed up to this point, there are no banks with an index efficiency value (H = 0.5). The bank with the highest Hurst value is Mouvement Desjardins (H = 0.84), proving to be the one with the highest degree of persistence, although it must be said that also for the other predictors the value obtained is very high. By contrast, the banks with the lowest Hurst index values are LCA Consultores (H = 0.46) and Renaissance Capital Holdings (H = 0.43), which have proven to be characterized by a slight anti-persistence. We are in a system where if the last observation is "up" it is likely that the next move is "down" and vice versa. The strength of this "anti-persistence" in the series is greater the closer it is to zero.

Table 8 - Coefficient Hurst Banks America

Bank	Specialisation	Sample size	Coefficient	Continent
Mouvement Desjardins	Commercial bank	128	0,84	America
Scotiabank	Commercial bank	563	0,83	America
Casa De Bolsa Ve Por Mas SA de CV	Commercial bank	88	0,82	America
JPMorgan Chase	Bank holding	571	0,82	America
Bank of America Corporation	Commercial bank	660	0,81	America
Citigroup	Bank holding	365	0,81	America
TD Securities	Investment bank	331	0,81	America
Prestige Economics LLC	Financial Services	164	0,81	America
Morgan Stanley	Commercial bank	476	0,80	America
Canadian Imperial Bank of Commerce	Commercial bank	752	0,80	America
ING Financial Markets	Investment bank	283	0,80	America
Lehman Brothers Inc.	Investment bank	152	0,79	America
Wells Fargo	Bank holding	410	0,79	America
Redtower	Financial Services	218	0,78	America
RBC Capital Markets	Investment bank	434	0,78	America
Paradigm Wealth Management	Financial Services	39	0,77	America
National Bank Financial	Commercial bank	314	0,77	America
Silicon Valley Bank	Commercial bank	203	0,76	America
Bank Of Montreal	Commercial bank	155	0,76	America
AFEX	Financial Services	33	0,76	America
Brown Brothers Harriman	Investment bank	48	0,73	America
Bank of New York Mellon	Commercial bank	18	0,71	America
Goldman Sachs Group	Bank holding	33	0,66	America
LCA Consultores	Financial Services	14	0,46	America
Renaissance Capital Holdings	Bank holding	10	0,43	America

This Table shows the Hurst coefficients calculated for each financial institution on the American continent and the sample size of the forecast on which the statistical test was applied. Highlighted in red, we report the financial institution with the highest value of the calculated index.

The banks of the European continent in Table 10 show the presence of a predictor that has an index value of H = 0.5, which is Raiffeisen. The behaviour of the institute is rational. This result demonstrates that even in the presence of a reduced sample size, the forecasts issued are efficient. Instead, with regard to the second-level analysis, the bank with the highest persistence value, which proves to have the highest coefficient of long-term memory among European institutions, is HSBC Holdings (H = 0.84).

On the contrary, among the banks with the highest anti-persistence values, we find MIG Investments (H = 0.0), Piraeus Bank Romania SA (H = 0.27), UFS Finance Investment Company (H = 0.06), WestLB (H = 0.10) and Credit Europe Bank (H = -0.50). These results demonstrate that future forecasts will be subject to a continuous alternation of movements, increasing or decreasing compared to forecasts issued in the past. This suggests that the five predictors will be characterized by being subject to high forecast volatility.

Table 9 - Coefficient of Hurst Banks Europe

Bank	Specialisation	Sample size	Coefficient	Continent
HSBC Holdings	Bank holding	545	0,84	Europe
Banco Santander	Commercial bank	146	0,83	Europe
Landesbank Baden-Wuerttemberg	Governmental credit institution	513	0,83	Europe
Credit Suisse Group AG	Bank holding	929	0,83	Europe
Erste Group Bank	Bank holding	382	0,82	Europe
CIB Bank	Commercial bank	240	0,81	Europe
Credit Agricole CIB	Bank holding	533	0,81	Europe
Danske Bank	Commercial bank	486	0,81	Europe
Saxo Bank	Securities firm	297	0,81	Europe
Swissquote Bank	Commercial bank	91	0,81	Europe
TMS Brokers	Financial Services	129	0,81	Europe
DNB Bank ASA	Commercial bank	118	0,81	Europe
Rabobank	Cooperative bank	403	0,81	Europe
Norddeutsche Landesbank	Governmental credit institution	125	0,81	Europe
Skandinaviska Enskilda Banken	Commercial bank	716	0,81	Europe
Deutsche Bank	Commercial bank	206	0,81	Europe
Bayerische Landesbank	Governmental credit institution	48	0,81	Europe
Cinkciarz.pl	Financial Services	88	0,80	Europe
Alpha Bank London Limited	Commercial bank	54	0,80	Europe
BNP Paribas	Commercial bank	522	0,80	Europe
Royal Bank of Scotland	Bank holding	393	0,80	Europe
ABB Ltd	Financial Services	62	0,79	Europe
Aletti Gestielle SGR	Financial Services	292	0,79	Europe
Barclays	Bank holding	706	0,79	Europe
Swedbank	Savings bank	112	0,79	Europe
Petrocommerce Bank	Commercial bank	207	0,79	Europe
Monex Europe Ltd	Financial Services	471	0,79	Europe
DZ Bank	Cooperative bank	212	0,79	Europe
Intesa Sanpaolo	Commercial bank	87	0,78	Europe
Banco Bilbao Vizcaya Argentaria	Commercial bank	281	0,78	Europe
Lloyds Bank Commercial Banking	Commercial bank	293	0,78	Europe
X-Trade Brokers Dom Maklerski	Financial Services	251	0,78	Europe
Investec	Commercial bank	187	0,78	Europe
Nordea Bank	Commercial bank	227	0,77	Europe

Nomura Bank International	Investment bank	150	0,77	Europe
AGEAS Finance NV	Finance company	80	0,77	Europe
Ebury Partners UK Ltd	Financial Services	147	0,77	Europe
Societe Generale	Commercial bank	276	0,76	Europe
Banca Monte dei Paschi di Siena S.p.A.	Commercial bank	172	0,76	Europe
Dresdner Bank AG	Commercial bank	195	0,75	Europe
Alpha Bank AE	Commercial bank	252	0,75	Europe
UniCredit	Commercial bank	269	0,75	Europe
UBS AG	Commercial bank	155	0,74	Europe
Argentex LLP	Financial Services	128	0,74	Europe
Banca Aletti & C spa	Commercial bank	83	0,73	Europe
Validus Risk Management	Financial Services	53	0,73	Europe
Natixis	Commercial bank	47	0,73	Europe
Commerzbank	Commercial bank	666	0,73	Europe
Alior Bank Spolka Akcyjna	Commercial bank	51	0,71	Europe
B. Metzler seel. Sohn & Co.	Bank holding	33	0,68	Europe
HBOS	Bank holding	56	0,68	Europe
HIFX PLC	Financial Services	25	0,66	Europe
Laurentian Bank of Canada	Commercial bank	14	0,65	Europe
Ceskoslovenska Obchodni Banka	Commercial bank	90	0,65	Europe
Standard Chartered	Bank holding	650	0,63	Europe
Hamilton Court FX LLP	Financial Services	40	0,62	Europe
Dom Maklerski AFS Sp zoo	Financial Services	20	0,62	Europe
4CAST	Financial Services	25	0,61	Europe
VTB Capital	Commercial bank	11	0,59	Europe
Bank Pekao SA	Commercial bank	24	0,58	Europe
KBC Groep	Bank holding	8	0,57	Europe
M2M Private Bank	Commercial bank	7	0,54	Europe
Advanced Currency Markets	Financial Services	20	0,52	Europe
Raiffeisen	Commercial bank	8	0,50	Europe
Piraeus Bank Romania SA	Commercial bank	4	0,27	Europe
WestLB	Investment & trust corporation	3	0,10	Europe
Investment Capital Ukraine	Financial Services	8	0,09	Europe
UFS Finance Investment Company	Financial Services	3	0,06	Europe
MIG Investments	Financial Services	4	0,00	Europe
Credit Europe Bank	Commercial bank	2	-0,50	Europe

This Table shows the Hurst coefficients calculated for each financial institution on the European continent and the sample size of the forecast on which the statistical test was applied. Highlighted in red, we report the financial institution with the highest value of the calculated index. The banks that have an efficient Hurst value are highlighted in red.

These results reflect what was achieved in the first chapter, where it was shown that revisions always tend to worsen the forecasts previously issued, rather than improve them (see Table 3). Predictors (see Table 4) would get a lower absolute value prediction error if they issued a prediction based on the random walk model. In addition, the forecast error increases as you approach the terminal date for which the forecast was issued, instead of decreasing. It follows that predictors demonstrate that they are unable to improve their mistakes. This can be demonstrated by the persistence results that characterize the financial institutions analysed.

In fact, as reported in Table Appendix A.3, the 91.67% of predictors has a Hurst coefficient value between 0.5 and 1. The 7.5% has a value between 0 and 0.5, and the remaining 0.83%, which is represented exclusively by the commercial bank Raiffeisen, which has a Hurst coefficient value of 0.5.

Table 10 - Percentage of efficiency or inefficiency

Range	Percentage	Classification
$0,5 < H < 1$	91,67%	Persistence
$H = 0,5$	0,83%	Efficient
$0 < H < 0,5$	7,5%	Antipersistence

This table shows the total percentages of the calculated Hurst coefficient, where we can observe that most of the analysed variables are characterized by a "Persistence" value. This confirms that predictors are not efficient. Hurst, between the variables checked.

For 91.67% of predictors, the forecasts are not independent among them. Past forecasts influence future forecasts. If the trend of time series has been positive in the past, it is likely that it will also be positive in the future and vice versa. The test allows us to affirm that the level of this persistence is greater the closer H is to the value of 1. Furthermore, if the historical series is characterized by the presence of trends that persist over time, the trend of a six-month period will influence the behaviour over the next six months, the same way a ten-year period will affect the other ten-year periods and so on.

Finally, using the idea developed by Sukpitak et al. (2016), it was decided to measure which financial intermediary recorded the greatest average deviation of its forecasts compared to the efficiency value of the known Hurst index (H = 0.5). The results shown in the table in Appendix A. 4, estimated for the horizon from the first quarter of 2007 to the second quarter of 2016, show that the banks with the largest average deviation from the efficiency value are

HSBC Holdings and Mouvement Desjardins (0,34). The same operation was also carried out for the average forecasts issued by the banks grouped by continent. The calculated difference will allow us to identify first which single bank, and then which continent have average forecasts closer to the efficiency threshold.

Table 11 - Difference Hurst Efficient coefficient by continent

Continent	Hurst coefficiet	Simple size	Efficient value	Difference
Africa	0,799	238	0,5	0,299
America	0,716	6462	0,5	0,216
Oceania	0,714	2088	0,5	0,214
Asia	0,697	1708	0,5	0,197
Europa	0,595	14131	0,5	0,095

This Table shows the percentage of the Hurst coefficient, calculated in averages for each continent, showing that the European continent represents the one with the lowest mead deviation from the efficient value of H=0,5.

The same operation was also carried out on the average of the forecasts issued by the banks grouped by continent: Africa, Asia, America, Europe and Oceania. The results in Table 11 show that the continent with the greatest average difference compared to the efficiency value of 0.5 is the African one (0.299), followed by America (0.216), Asia (0.214), Oceania (0.197) and Europe (0.095). So, the European continent is the one that comes closest to the efficiency value, a symptom of a lower average error in the horizon considered. This result shows that Europe has a better predictive capacity than that of the other predictors considered, which leads us to ask ourselves if there is a leader in the euro-dollar exchange rate market that demonstrates the existence of a cause and effect relationship between the individual banks, or between the five continents of the Bloomberg dataset available. We will address this topic in the fourth chapter of this dissertation through the use of the Toda and Yamamoto test (1995).

3.4 Conclusion

The results obtained through the application of the Hurst coefficient to the historical series of financial institutions of the Bloomberg dataset available, as stated by Mandelbrot et al. (1968), show that investors, both professional and non-professional, are never efficient. The test, applied to the time series of all available predictors, shows that the average of the forecasts, calculated for each of the 120 variables to be analysed, are not consistent with the mathematical expectations based on the calculation of the probabilities, which aims to achieve the maximum possible satisfaction. With the exception of the financial company Raffeisen, which proves to have a value of the Hurst coefficient equal to 0.5, there are no other variables that present efficiency values. It should also be said that the result achieved by Raffeisen cannot be considered completely reliable due to the limited sample size on which the test was made, corresponding to only 8 forecasts and/or revisions (see in the table in Appendix A.3).

Furthermore, as reported in Table 10, 91.67% of financial institutions exhibit "persistent" behaviour. This means that if the trend of the time series has been positive in the last period, it is probable that it will also be positive in the following period and vice versa. The level of this persistence is greater the closer H is to the value of 1 (see table in Appendix A.3). Hence, the historical series is characterized by the presence of trends that persist over time. The performance of a six-month period influences the behaviour in the subsequent six-month periods, just as a ten-year period influences the other ten-year periods and so on.

This allows us to say that there is a very high probability that if predictors were inefficient in the past, they will also be inefficient in the future. The link between the past and the future of each individual financial institution is difficult to forget. It follows that, as in the past, also in the future predictors will tend to be inefficient, due to the inability to absorb new information as it becomes known, in the time course leading to the terminal date for which the forecast or revision has been issued. Furthermore, all cognitive biases, which systematically alter the rationality of our investment choices, will tend to persist, continuing to accentuate the forecast error, placing a strong limit on the ability to use the mistakes made in the past to learn and avoid making mistakes in the future.

Finally, the estimate made on the average of the forecasts issued by the banks grouped by continent has shown that the European one is the one with the smallest average forecast error, compared to the efficiency value of H = 0.5, as shown in the Table 11 (Africa (0.299), America (0.216), Asia (0.214), Oceania (0.197) and Europe (0.095)).

This result, which shows that Europe has a better predictive capacity than that of the other predictors considered, represents the connection with the fourth and final chapter of this dissertation, which leads us to ask ourselves if Europe, and / or the European banks, will represent the market leader in the euro-dollar exchange rates. Is there a herd effect that pushes banks towards a common prediction, as shown by the inefficiency results of 99.17% of the predictors that have been analysed through the Hurst test, as shown in Table 11? Can everything be reduced to a simple phenomenon of randomness? We will deal with this topic in the fourth chapter of this thesis through the use of the Toda and Yamamoto test (1995).

Appendix A. 3 - Hurst coefficient value calculated for each predictor

Bank	Numerosità Campionaria	Hurst Coefficient	Continent
Credit Suisse Group AG	929	0,83	Europe
Canadian Imperial Bank of Commerce	752	0,80	America
Skandinaviska Enskilda Banken	716	0,81	Europe
Barclays	706	0,79	Europe
Commerzbank	666	0,73	Europe
Bank of America Corporation	660	0,81	America
Standard Chartered	650	0,63	Europe
JPMorgan Chase	571	0,82	America
Scotiabank	563	0,83	America
National Australian Bank Limited	561	0,81	Oceania
HSBC Holdings	545	0,84	Europe
Credit Agricole CIB	533	0,81	Europe
BNP Paribas	522	0,80	Europe
Landesbank Baden-Wuerttemberg	513	0,83	Europe
Danske Bank	486	0,81	Europe
Commonwealth Bank of Australia	477	0,78	Oceania
Morgan Stanley	476	0,80	America
Monex Europe Ltd	471	0,79	Europe
Westpac Banking	463	0,81	Oceania
RBC Capital Markets	434	0,78	America
Wells Fargo	410	0,79	America
Rabobank	403	0,81	Europe
Royal Bank of Scotland	393	0,80	Europe
Erste Group Bank	382	0,82	Europe
Citigroup	365	0,81	America
Mitsubishi UFJ Financial Group	351	0,77	Asia
TD Securities	331	0,81	America
Australia & New Zealand Banking Group	318	0,74	Oceania
National Bank Financial	314	0,77	America
Saxo Bank	297	0,81	Europe
Lloyds Bank Commercial Banking	293	0,78	Europe
Aletti Gestielle SGR	292	0,79	Europe
ING Financial Markets	283	0,80	America
Banco Bilbao Vizcaya Argentaria	281	0,78	Europe
Sumitomo Mitsui Trust Bank	279	0,73	Asia
Societe Generale	276	0,76	Europe
UniCredit	269	0,75	Europe
Alpha Bank AE	252	0,75	Europe
X-Trade Brokers Dom Maklerski	251	0,78	Europe
CIB Bank	240	0,81	Europe

Nordea Bank	227	0,77	Europe
Redtower	218	0,78	America
DZ Bank	212	0,79	Europe
Petrocommerce Bank	207	0,79	Europe
Deutsche Bank	206	0,81	Europe
Silicon Valley Bank	203	0,76	America
Dresdner Bank AG	195	0,75	Europe
Oversea-Chinese Banking Corp	193	0,80	Asia
Investec	187	0,78	Europe
Standard Bank Group	179	0,76	Africa
Vadilal Forex	175	0,77	Asia
Banca Monte dei Paschi di Siena S.p.A.	172	0,76	Europe
Prestige Economics LLC	164	0,81	America
BMO Capital Markets	155	0,76	America
UBS AG	155	0,74	Europe
Lehman Brothers Inc.	152	0,79	America
Nomura Bank International	150	0,77	Europe
Ebury Partners UK Ltd	147	0,77	Europe
Banco Santander	146	0,83	Europe
Bank of New Zealand	146	0,73	Oceania
SJS Markets Limited	130	0,71	Asia
TMS Brokers	129	0,81	Europe
Mouvement Desjardins	128	0,84	America
Malayan Banking Berhad	128	0,82	Asia
Argentex LLP	128	0,74	Europe
Norddeutsche Landesbank	125	0,81	Europe
DNB Bank ASA	118	0,81	Europe
Swedbank	112	0,79	Europe
Emirates NBD PJSC	105	0,77	Asia
Swissquote Bank	91	0,81	Europe
Ceskoslovenska Obchodni Banka	90	0,65	Europe
Casa De Bolsa Ve Por Mas SA de CV	88	0,82	America
Cinkciarz.pl	88	0,80	Europe
Intesa Sanpaolo	87	0,78	Europe
Macquarie Bank	86	0,80	Oceania
Banca Aletti & C spa	83	0,73	Europe
Ageas Finance NV	80	0,77	Europe
HDFC Bank LTD	79	0,76	Asia
ICICI Bank	65	0,73	Asia
ABB Ltd	62	0,79	Europe
DAY Bank	59	0,79	Asia
Rand Merchant Bank	56	0,80	Africa
HBOS	56	0,68	Europe

Alpha Bank London Limited	54	0,80	Europe
Validus Risk Management	53	0,73	Europe
Alior Bank Spolka Akcyjna	51	0,71	Europe
Brown Brothers Harriman	48	0,73	America
Mecklai Financial Services	48	0,60	Asia
Bayerische Landesbank	48	0,81	Europe
Natixis	47	0,73	Europe
Hamilton Court FX LLP	40	0,62	Europe
Paradigm Wealth Management	39	0,77	America
St George Bank	37	0,65	Oceania
AFEX	33	0,76	America
Goldman Sachs Group	33	0,66	America
B. Metzler seel. Sohn & Co.	33	0,68	Europe
RHB OSK Securities	26	0,76	Asia
4CAST	25	0,61	Europe
HIFX PLC	25	0,66	Europe
Bank Pekao SA	24	0,58	Europe
CIMB Group	22	0,73	Asia
Advanced Currency Markets	20	0,52	Europe
Dom Maklerski AFS Sp zoo	20	0,62	Europe
IDEAglobal	19	0,64	Asia
Bank of New York Mellon	18	0,71	America
LCA Consultores	14	0,46	America
Laurentian Bank of Canada	14	0,65	Europe
Yes Bank	11	0,60	Asia
VTB Capital	11	0,59	Europe
Renaissance Capital Holdings	10	0,43	America
Investment Capital Ukraine	8	0,09	Europe
KBC Groep	8	0,57	Europe
Raiffeisen	8	0,50	Europe
M2M Private Bank	7	0,54	Europe
MIG Investments	4	0,00	Europe
Piraeus Bank Romania SA	4	0,27	Europe
FXPRIMUS Ltd	3	0,10	Africa
UFS Finance Investment Company	3	0,06	Europe
WestLB	3	0,10	Europe
Credit Europe Bank	2	-0,50	Europe

This Table shows the Hurst coefficients calculated for each financial institution available in the Bloomberg dataset analysed, during the horizon from the first quarter of 2007 to the second quarter of 2016. Furthermore, predictors are shown in descending order, based on the number of samples, which corresponds to the number of average forecasts issued. In red, the only bank with an efficient Hurst value has been reported among the verified variables, although it must be said that the result is not reliable for the purpose of the analysis due to the limited sample size that characterizes it.

Appendix A. 4 – Difference in Hurst average forecast value and efficient value

Bank	Hurst coefficiet	Simple size	Efficient value	Difference
HSBC Holdings	0,84	545	0,5	0,34
Mouvement Desjardins	0,84	128	0,5	0,34
Scotiabank	0,83	563	0,5	0,33
Banco Santander	0,83	146	0,5	0,33
Landesbank Baden-Wuerttemberg	0,83	513	0,5	0,33
Credit Suisse Group AG	0,83	929	0,5	0,33
Casa De Bolsa Ve Por Mas SA de CV	0,82	88	0,5	0,32
Malayan Banking Berhad	0,82	128	0,5	0,32
JPMorgan Chase	0,82	571	0,5	0,32
Erste Group Bank	0,82	382	0,5	0,32
CIB Bank	0,81	240	0,5	0,31
Bank of America Corporation	0,81	660	0,5	0,31
Citigroup	0,81	365	0,5	0,31
Credit Agricole	0,81	533	0,5	0,31
Danske Bank	0,81	486	0,5	0,31
Saxo Bank	0,81	297	0,5	0,31
TD Securities	0,81	331	0,5	0,31
National Australian Bank Limited	0,81	561	0,5	0,31
Swissquote Bank	0,81	91	0,5	0,31
TMS Brokers	0,81	129	0,5	0,31
DNB Bank ASA	0,81	118	0,5	0,31
Rabobank	0,81	403	0,5	0,31
Norddeutsche Landesbank	0,81	125	0,5	0,31
Skandinaviska Enskilda Banken	0,81	716	0,5	0,31
Deutsche Bank	0,81	206	0,5	0,31
Westpac Banking	0,81	463	0,5	0,31
Bayerische Landesbank	0,81	48	0,5	0,31
Prestige Economics LLC	0,81	164	0,5	0,31
Rand Merchant Bank	0,80	56	0,5	0,30
Cinkciarz.pl	0,80	88	0,5	0,30
Morgan Stanley	0,80	476	0,5	0,30
Canadian Imperial Bank of Commerce	0,80	752	0,5	0,30
Alpha Bank London Ltd	0,80	54	0,5	0,30
Oversea-Chinese Banking Corp	0,80	193	0,5	0,30
BNP Paribas	0,80	522	0,5	0,30
Royal Bank of Scotland	0,80	393	0,5	0,30
Macquarie Bank	0,80	86	0,5	0,30
ING Financial Markets	0,80	283	0,5	0,30
ABB Ltd	0,79	62	0,5	0,29
Aletti Gestielle SGR	0,79	292	0,5	0,29
Barclays	0,79	706	0,5	0,29
Swedbank	0,79	112	0,5	0,29
Petrocommerce Bank	0,79	207	0,5	0,29

Lehman Brothers Inc.	0,79	152	0,5	0,29
DAY Bank	0,79	59	0,5	0,29
Monex Europe Ltd	0,79	471	0,5	0,29
Wells Fargo	0,79	410	0,5	0,29
DZ Bank	0,79	212	0,5	0,29
Intesa Sanpaolo	0,78	87	0,5	0,28
Banco Bilbao Vizcaya Argentaria	0,78	281	0,5	0,28
Lloyds Bank Commercial Banking	0,78	293	0,5	0,28
X-Trade Brokers Dom Maklerski	0,78	251	0,5	0,28
Commonwealth Bank of Australia	0,78	477	0,5	0,28
Investec	0,78	187	0,5	0,28
Redtower	0,78	218	0,5	0,28
RBC Capital Markets	0,78	434	0,5	0,28
Emirates NBD PJSC	0,77	105	0,5	0,27
Nordea Bank	0,77	227	0,5	0,27
Nomura Bank International	0,77	150	0,5	0,27
Ageas Finance NV	0,77	80	0,5	0,27
Paradigm Wealth Management	0,77	39	0,5	0,27
Ebury Partners UK Ltd	0,77	147	0,5	0,27
National Bank Financial	0,77	314	0,5	0,27
Vadilal Forex	0,77	175	0,5	0,27
Mitsubishi UFJ Financial Group	0,77	351	0,5	0,27
Silicon Valley Bank	0,76	203	0,5	0,26
RHB OSK Securities	0,76	26	0,5	0,26
HDFC Bank LTD	0,76	79	0,5	0,26
Standard Bank Group	0,76	179	0,5	0,26
Bank Of Montreal	0,76	155	0,5	0,26
Societe Generale	0,76	276	0,5	0,26
Banca Monte dei Paschi di Siena S.p.A.	0,76	172	0,5	0,26
Afex	0,76	33	0,5	0,26
Dresdner Bank AG	0,75	195	0,5	0,25
Alpha Bank AE	0,75	252	0,5	0,25
UniCredit	0,75	269	0,5	0,25
Australia & New Zealand Banking Group	0,74	318	0,5	0,24
UBS	0,74	155	0,5	0,24
Argentex LLP	0,74	128	0,5	0,24
Bank of New Zealand	0,73	146	0,5	0,23
Brown Brothers Harriman	0,73	48	0,5	0,23
CIMB Group	0,73	22	0,5	0,23
Banca Aletti & C spa	0,73	83	0,5	0,23
Validus Risk Management	0,73	53	0,5	0,23
Sumitomo Mitsui Trust Bank	0,73	279	0,5	0,23
Natixis	0,73	47	0,5	0,23
Commerzbank	0,73	666	0,5	0,23
ICICI Bank	0,73	65	0,5	0,23
Alior Bank Spolka Akcyjna	0,71	51	0,5	0,21
Bank of New York Mellon	0,71	18	0,5	0,21

SJS Markets Limited	0,71	130	0,5	0,21
B. Metzler seel. Sohn & Co.	0,68	33	0,5	0,18
Hbos	0,68	56	0,5	0,18
Goldman Sachs Group	0,66	33	0,5	0,16
HIFX PLC	0,66	25	0,5	0,16
St George Bank	0,65	37	0,5	0,15
Laurentian Bank of Canada	0,65	14	0,5	0,15
Ceskoslovenska Obchodni Banka	0,65	90	0,5	0,15
IDEAglobal	0,64	19	0,5	0,14
Standard Chartered	0,63	650	0,5	0,13
Hamilton Court FX LLP	0,62	40	0,5	0,12
Dom Maklerski AFS Sp zoo	0,62	20	0,5	0,12
4CAST	0,61	25	0,5	0,11
Mecklai Financial Services	0,60	48	0,5	0,10
Yes Bank	0,60	11	0,5	0,10
VTB Capital	0,59	11	0,5	0,09
Bank Pekao SA	0,58	24	0,5	0,08
KBC Groep	0,57	8	0,5	0,07
M2M Private Bank	0,54	7	0,5	0,04
Advanced Currency Markets	0,52	20	0,5	0,02
Raiffeisen	0,50	8	0,5	0,00
LCA Consultores	0,46	14	0,5	-0,04
Renaissance Capital Holdings	0,43	10	0,5	-0,07
Piraeus Bank Romania SA	0,27	4	0,5	-0,23
FXPRIMUS Ltd	0,10	3	0,5	-0,40
WestLB	0,10	3	0,5	-0,40
Investment Capital Ukraine	0,09	8	0,5	-0,41
UFS Finance Investment Company	0,06	3	0,5	-0,44
MIG Investments	0,00	4	0,5	-0,50
Credit Europe Bank	-0,50	2	0,5	-1,00

This table shows the average deviation calculated for the time series of the variables available in the analysed Bloomberg dataset. The displacement was calculated by the difference between the average predictions of each predictor in the horizon considered and the efficient value of H = 0.5.

CHAPTER IV

Is there a leader who dominates the exchange rate market?

4.1 Hypotheses development and motivation analysis

The aim of this chapter is to demonstrate whether Granger causality exists among the time series of the 120 banks in the Bloomberg dataset available, which concerns forecasts and revisions in euro-dollar currency, in the horizon from 2007 to 2016, for 120 banks divided between the five continents: Europe, Asia, America, Africa and Oceania. To demonstrate that the forecasts issued by the financial intermediaries analysed are not random, but follow a temporal issuance scheme, it was decided to use the modified test of Toda and Yamamoto (1995). An important feature of the test is that the variables to be analysed do not have to be previously standardized. Therefore, time series can be integrated with different orders, cointegrated, non-cointegrated or both. This type of approach has greatly simplified the application of the test compared to the more traditional Granger non-causality test, eliminating the problem of testing the cointegration or the conversion of VAR to ECM.

We use the modified Granger causality test by Toda and Yamamoto (1995) to measure whether between the historical series of the financial intermediaries being analysed, there is a cause and effect relationship that allows us to affirm that one or more predictors systematically issue in advance their forecasts, compared to all the others. This would allow us to say that there is a leader in the euro-dollar exchange rate market among the 120 banks analysed. The results achieved through the application of the Toda Yamamoto test (1995) have shown that the historical series of the first 5 banks, according to the asset and equity ranking updated to 2007, the year of the beginning of our analysis, behave as market leaders in the whole horizon considered. The existence of Granger causality allows us to confirm the results achieved by a group of researchers from the Federal Institute of Technology in Zurich, Switzerland, who, analysing the transnational relationships between 43,030 multinational companies, have shown that there are 147 companies, mainly the banks, called "superentities", which collectively hold 40% of the total wealth of the entire network of transnational exchanges. This study, published by Andy Coghlan and Debora MacKenzie in the New Scientist magazine in 2011, demonstrates the existence of a connection with banks in our dataset. In fact, scrolling through the list of "superentities" shown in the table in the appendix (Appendix A.6), we can find a sufficiently large number of predictors in common, confirming our theory.

Furthermore, further data supporting our analysis is represented by the news of the maxi fine issued by the European Antitrust Authority to a group of banks for having created a real "cartel" on the foreign exchange market (2019). This operation involved eleven currencies, including the British pound, the Yen, the Swiss franc, the Euro, the United States, Canadian, New Zealand and the Australian dollar and the Danish, Swedish and Norwegian krone. Scrolling the names of the fined banks, we find five of the ten banks that behave as market leaders in the exchange rates in euro-dollar currency in our dataset: Barclays, Royal Bank of Scotland, Citigroup, JPMorgan and MUFG Bank. This result highlights how the existence of a "cartel" on the currency markets had existed for some time before, and the fine issued by the European Antitrust represents only the conclusion of a leadership which allows to confirm and validate the outcome of our results.

4.2 Literature Review

In literature, the Toda and Yamamoto (1995) test has been used to demonstrate the existence of a cause and effect relation between a plurality of economic and financial variables. This happens at both an aggregate and disaggregated level, and includes interest rates and share prices, bitcoin and equity indices, expected inflation and nominal interest rates, exchange rates and inflation, share and trading prices, taxation and governance and export and productivity. However, as far as we know, we are still not used to studying, as in our case, whether there are leaders in the foreign exchange market.

The test developed by Toda and Yamamoto in 1995 is a simplification of the Granger causality test (1969), since it does not require the standardization of the variables to be analysed. It is very useful for measuring the dependence between time series in VAR in reduced form. As already mentioned previously, it is widely used in literature to examine whether the delayed values of a variable help to predict another, as demonstrated by the studies of Stock and Watson (2001)[11].

A VAR is a multi-equation and multi-variable linear model in which each variable is in turn explained by its own delayed values, as well as by the current and past values of the remaining variables. Compared to a univariate self-regression, VARs provide both a systematic way to capture rich dynamics in multiple time series, and a coherent and credible approach to prediction. This statistical model used to study the existence of a causal

[11] See James, S.H., and Watson., M.W. (2001).

relationship between two variables foresees the estimation of the following simple vector autoregressions (VAR):

$$X_t = \sum_{i=1}^{n} \alpha_i Y_{t-i} + \sum_{j=1}^{n} \beta_j X_{t-j} + \mu_{1t} \ (5)$$

$$Y_t = \sum_{i=1}^{m} \lambda_i X_{t-i} + \sum_{j=1}^{n} \delta_j Y_{t-j} + \mu_{2t} \ (6)$$

where it is assumed that the disturbances μ_{1t} and μ_{2t} are not related. Equation (5) indicates that the variable X is decided by the delayed variables Y and X. The same thing happens for equation (6) except that its dependent variable is Y rather than X. Therefore, if causality exists, it means that Y delayed significantly influences X in equation (5) and X delayed significantly influences Y in equation (6). Causality is a phenomenon closely related to the idea of cause and effect, although it is not exactly the same. A variable X is causal to the variable Y if X is the cause of Y or Y is the cause of X. However, applying the Toda and Yamamoto test, we are not measuring a true cause-effect relationship, but rather what we want to know is whether a particular variable anticipates another in the time series. In other words, we want to show that the connection between two variables is not causal in the true sense of the word. When econometricians say "cause", what they mean is "cause-Granger", although a more appropriate word may be "precedent" (Leamer, 1985).

The Toda and Yamamoto test is easy to perform and can be applied in many types of empirical studies. It has exceeded the limits of the traditional Granger Causality test, as pointed out by Gujarati (1995), which states that a two-variable causality test is sensitive to model specifications and the number of delays. According to Maddala (2001)[12], time series data are often non-stationary, demonstrating the problem of spurious regression, as also stated by Huang, Kao et al. (2004). Furthermore, Gujarati (2006) also stated that if the variables are integrated, the statistical test procedure F is invalid, since the test statistics do not have a standard distribution[13]. Although researchers can still test the meaning of individual coefficients with t-statistics, the F-statistic cannot be used to jointly test Granger's non-causality.

Since the Granger causality test is based on stationary hypotheses, it is not valid in the presence of instability, becoming unreliable, with the risk of leading to an incorrect inference, as demonstrated by Stock and Watson (1996, 1999, 2003, 2006), Rossi (2013), Clark and McCracken (2006), Boivin and Giannoni (2006), Kozicki and Tinsley (2001) and Cogley and Sargent (2001, 2005).

To overcome these problems, Toda and Yamamoto (1995) and Dolado and Lutkepohl (1996) proposed a modified test for Granger causality that is not based on standardization of variables[14]. The test foresees the estimation of an increased VAR regardless of whether the series is cointegrated or non-cointegrated, see also Wolde-Rufael (2005). This approach greatly simplifies the causality of Granger as we do not need to test the cointegration or convert VAR to ECM[15].

12 See Maddala, G.S. (2001).

13 See Gujarati, D.N. (2006).

14 See Lütkepohl, H., and Poskitt, D.S. (1996).

15 See Toda, H.Y., and Yamamoto T. (1995).

Granger's simplified test, to study the existence of causality, has been applied to a large number of macroeconomic variables, with the aim of trying to make sense of the relationships that connect and influence the performance of the economy and finance. Among these we can mention Gharana et al. (2011), who used the Toda-Yamamoto-Dolado-Lutkephol Augmented VAR (p) technique to test the causality of Granger, as through this test it is possible to obtain more solid and asymptotically reliable results. The analysis, which is concentrated in the post-liberalization period, allows us to say that Chinese economic growth is Granger caused by exports., Imports, on the otherhand, while not showing that they have Granger causality towards GDP, influence the indirect channel which in turn influences exports and foreign investment.

Amiri et al. (2012), used the Granger causality test proposed by Toda and Yamamoto to analyse the causality between GDP and health spending in OECD countries, obtaining results demonstrating a bidirectional Granger causality.

Others such as Abdul Manap et al. (2012) analysed the causal relationship between Islamic banking development and economic growth and between Islamic banking development and capital formation in the case of Malaysia. They use the Toda-Yamamoto test and the bootstrap test to reduce dimensional distortion in the data and provide more precise inference. The results show that there is greater causality between Islamic financial development and economic growth. In addition, the study shows that further growth in Islamic finance will be achieved as a result of Malaysia's economic growth.

Bakar et al. (2014) examined the causal relationship between education and economic growth in Malaysia, using data from the annual time series from 1975 to 2013. The Toda-Yamamoto causality test was used to investigate the direction of causality between variables, showing that there is a causality bidirectional ranging from economic growth to education and from education to economic growth.

Ghosh et al. (2014) analysed the dynamic linear and non-linear impact of oil price shocks on macroeconomic foundations for an emerging oil-importing economy, such as India, in the period from 1991 to 2009. The results, using the model proposed by Toda and Yamamoto note that inflation and the currency reserve are heavily influenced by oil price shocks. The movement in oil prices is exogenous compared to the movement of macroeconomic variables in India and the impact of oil price shocks is asymmetrical in nature with negative price shocks that have a more pronounced effect than positive shocks.

Akkas et al. (2015) analysed the causality between house prices and the interest rate on mortgages, in the period from 2010 to 2015. The results of the causality test Toda-Yamamoto (1995) which overcomes the problems of the standard causality test of Granger (1969), revealed a one-way causality between the mortgage interest rate and the house price index, where the former Granger causes the latter. The reverse is incorrect.

Okafor et al. (2016) analysed the annual data of the CBN statistical bulletin to determine the relationship between the inflow of foreign capital and economic growth in Nigeria in the period from 1981 to 2014. The results achieved through the application of the Toda and Yamamoto tests revealed that there is a bidirectional causality ranging from GDP to FDI, as well as from FDI to GDP. Furthermore, they have shown that there is one-way causality between FPI and GDP with causality ranging from FPI to GDP and between GDP and FA with causality ranging from FA to GDP. Finally, the joint causality between all components of the inflow of foreign capital, i.e. FDI, FPI, FA and GDP, indicates that an increase in the inflow of foreign capital positively increases GDP.

Abinaya et al. (2016) analysed the existence of a Granger causality relationship between stock prices and trading volume using minute by minute data of companies traded at the National Stock Exchange in India for the period of one year from July 2014 to June 2015. Since the time series data taken is not integrated in the same order, the Toda-Yamamoto methodology was applied to test for causality. The results show that 29 out of the 50 companies have two-way (bi-directional) causality between price and volume, and 15 companies have a one way (unidirectional) causal relationship, where price causes volume but volume does not cause price. Six other companies have no causal relationship in either way. The study suggests that the Efficient Market Hypothesis does not hold true for these 29 companies during the period of this study.

Dritsaki (2017), analysed the relationship between inflation and nominal interest rates for three European countries, such as Germany (member of EMU), Great Britain (ex-member country of the) and Switzerland (a non-EU country), in a temporal arc from 1995 to 2015. To test the long-term equilibrium relationship, they used different approaches including

Granger's non-causality approach developed by Toda and Yamamoto (1995) in a two-variable vector auto-regression model. The results achieved showed that the nominal interest rate influences large-scale inflation in the three countries analysed, while inflation only affects the interest rate in Germany.

Yola et al. (2018), analysed the causal relationship between the three largest African stock markets in Nigeria, South Africa and Egypt. The analysis was conducted through the robust causality test of Toda and Yamamoto (1995) on two distinct samples. The first sample used the index market share index during the horizon from 2000 until April 2008 (pre-crisis period). The second sample concerned the period of crisis\post crisis, which runs from May 2008 until the end of 2016. The results of the two applications have shown that in the pre-crisis period there are no relationships of Granger causality between the equity holders of the three markets. In the period of crisis\post crisis, a one-way Granger causality relationship was highlighted, going from South Africa to Nigeria, but at the same time there were no causal relationships between the stock exchange markets.

Dlamini (2019) analysed the causal relationship between the Lilangeni dollar exchange rate and the price of crude oil, using the Toda and Yamamoto (1995) approach. From January 2005 to April 30 2018, they analysed the daily data of the nominal exchange rate of the Lilangeni (Eswatini currency [SZL]) versus the US dollar (USD) data and the global price of Brent crude oil data that was used as a proxy for the global crude oil price. The results showed that there is a one-way causality ranging from the global oil price to the nominal exchange rate of Eswatini (SZL / USD). It follows that the global crude oil price influences the nominal exchange rate of Eswatini.

Dlamini (2019) et al. he also analysed the causal relationship between sugar exchange and economic growth in the Kingdom of Eswatini, using a quarterly dataset from 2005 to 2017. The analysis was conducted through the Toda-Yamamoto test (1995). The test results showed that the exchange of sugar led to economic growth, but economic growth is not caused by the exchange of sugar, which means that there is one-way causality.

Saliminezhad et al. (2020) analysed the impact of the manufacturing sector's commercial constraints on economic growth in South Africa in the period from 1987 to 2016, through the new Fourier Toda-Yamamoto method. This takes into account the structural changes in a causality analysis, since when using the traditional Toda and Yamamoto test, Granger causality was not found due to structural interruptions that generate errors. The results showed that Granger's one-way causality exists, ranging from the production environment index to economic growth.

Our study innovates literature for the use of a dataset extracted from the newly used Bloomberg platform, which deals with the forecasts and revisions of the exchange rates in euro-dollar currency for 120 banks divided among the five continents: Europe, Asia, America, Africa and Oceania. We use the modified Granger causality test by Toda and Yamamoto (1995) to test whether among the aforementioned banks there are one or more market leaders who systematically issue their forecasts in advance, compared to all the others. At the same time, the existence of causality between the historical series being analysed, allows us to demonstrate another truth: although the predictions issued by all the predictors are inefficient, as demonstrated in the previous chapter of this dissertation (see chapter 3) through the application of the Hurst index, predictors in general prefer to follow the forecasts issued by one or more market leaders. Why is this? Are predictors not able to make mistakes on their own? Is there a flock effect on forecast errors?

To answer these questions, we report the experiment carried out by Solomon E. Asch (1952), who, in his work "Social Psychology" has shown that the judgment of others has a very high specific weight on our self-esteem, which pushes us to follow a flock effect, believing that homologation protects us from criticism. The author, to demonstrate the existence of this phenomenon, specifically carried out an experiment on a group of individuals. He first divided them into small groups, and then into each of these groups he inserted five of his collaborators, who had the task of giving deliberately wrong answers. The goal was to demonstrate how the other members of the group in 40% of cases tended to issue the same responses as the collaborators, even if aware that they were incorrect. This explains why even if they are aware of the risk of a possible market crash, as in the case of a speculative bubble, investors choose to follow the "speculators" rather than get out of the flock and save their investment in time. This phenomenon represents one of the many mental traps, known as heuristics, which limit the veracity of classical theory to the advantage of behavioural theory. The flock effect pushes individuals to act like the mass, without thinking about their specific personal needs.

4.3 Application Methodology[16]

Toda and Yamamoto (1995) developed a cause-and-effect test in which the variables to be analysed do not have to be previously standardized. Therefore, time series can be integrated with different orders, cointegrated, non-cointegrated or both. This type of approach has greatly simplified Granger's non-causality test by eliminating the problem of testing the cointegration or conversion of VAR to ECM.

The application of the statistical test by Toda and Yamamoto (1995) to the time series of the Bloomberg data set being analysed, was carried out through the use of the Stata statistical software. Before proceeding with the application, we averaged the forecasts for each predictor in order to have four average annual forecasts for each of them. The forecasts issued in our dataset have a quarterly frequency. Therefore, the average of the forecasts will be quarterly, and each quarter will include the first forecast and all revisions of the first forecast issued and performed by each bank in the period leading to the terminal date for which the forecast was made.

For each financial institution, we can obtain up to a maximum of 38 average forecasts during the horizon from 2007 to the second quarter of 2016. Furthermore, unlike the first and second chapters, we have been able to extend the time horizon by a further six months, because the date for which the forecast was issued (end date) was used as the reference metric. The quarterly forecasts for each predictor have been calculated, because otherwise if we insert the same date more than once in the test, the Stata software, will not work correctly, giving us an error message.

[16] For a detailed description of the dataset used in the analysis of chapter 3, please see par. 1.2.

After calculating the quarterly average of the forecasts, the sample size of each variable in the dataset has been significantly reduced, but this allows us to have a dataset without holes, which causes the loss of important data.

The Granger causality test increased by Toda and Yamamoto (1995) is based on the following equations:

$$Y_t = \mu + \sum_{i=1}^{p+m} \alpha_i Y_{t-i} + \sum_{i=1}^{p+m} \beta_i X_{t-i} + u_{1t} \quad (7)$$

$$X_t = \mu + \sum_{i=1}^{p+m} \gamma_i X_{t-i} + \sum_{i=1}^{p+m} \delta_i Y_{t-i} + u_{2t} \quad (8)$$

where m is the maximum integration order of the variable in the system and p is the optimal delay length of Y_t and X_t and it is assumed that the error terms are white noise, ~ (0, σ2) and not autocorrelation. We need to determine the maximum integration order m, which we expect to occur in the model and construct a VAR in their levels with a total of (p + m) delays.

There are some basic steps we need to follow to run the Toda-Yamamoto test[17]:

- Step 1 = Test each time series to determine their integration order. Ideally, this should involve the use of a test (such as the ADF test) for which the null hypothesis is non-stationary[18]; as well as a test (like the KPSS test) for which the null hypothesis is stationary. It is good to cross check;

17 See Toda, H.Y., and Yamamoto T. (1995).

18 See Dickey, D.A., and Fuller, W.A. (1979).

- Step 2 = Let the maximum integration order for the time series group be m '. So if there are two time series and one cause the other, then m ′ = 2m ′ = 2. If one is I (0) and the other is I (1), then m ′ = 1m ′ = 1, etc.;
- Step 3 = Set a VAR model in the data levels, regardless of the integration orders of the various time series. More importantly, we must not differentiate the data, regardless of what we found in step 1;
- Step 4 = Determine the appropriate maximum delay length for the variables in the VAR, p′, using the usual methods. In particular, base the choice of p′ on the usual information criteria, such as AIC, SIC:

$$Y_t = \mu + \sum_{i=1}^{p'} \alpha_i Y_{t-i} + \sum_{i=1}^{p'} \beta_i X_{t-i} + u_{1t} \quad (9)$$

$$X_t = \mu + \sum_{i=1}^{p'} \gamma_i X_{t-i} + \sum_{i=1}^{p'} \delta_i Y_{t-i} + u_{2t} \quad (10)$$

- Step 5 = Make sure the VAR is well specified. For example, make sure that there is no serial correlation between the residues. If necessary, increase the p until the resolution of any autocorrelation problems;
- Step 6 = Now take the preferred VAR model and add in m′ additional delays (from Step 2) of each of the variables in each of the equations:

$$Y_t = \mu + \sum_{i=1}^{p'+m'} \alpha_i Y_{t-i} + \sum_{i=1}^{p'+m'} \beta_i X_{t-i} + u_{1t} \quad (11)$$

$$X_t = \mu + \sum_{i=1}^{p'+m'} \gamma_i X_{t-i} + \sum_{i=1}^{p'+m'} \delta_i Y_{t-i} + u_{2t} \quad (12)$$

- Step 7 = Check the non-causality of Granger as follows. Check the hypothesis that the p coefficients of the (only) first delayed X_t values are zero in the Y_t equation using a standard Wald test. Then, do the same thing for the coefficients of the delayed Y_t values in the X_t equation. Then test the null hypothesis and the alternative hypothesis of X_t in the Y_t and Y_t equation in the X_t equation in the following way:

$$H0: \sum_{i=1}^{p'} \beta_i = 0 \rightarrow Xt\ non\ causa\ Y_t\ ; (13)$$

$$H0: \sum_{i=1}^{p'} \beta_i \neq 0 \rightarrow Xt\ causa\ Y_t;\ (14)$$

$$H0: \sum_{i=1}^{p'} \delta_i = 0 \rightarrow Yt\ non\ causa\ X_t; (15)$$

$$H0: \sum_{i=1}^{p'} \delta_i \neq 0 \rightarrow Yt\ causa\ X_t;\ (16)$$

- Step 8 = It is essential that we do not include the coefficients for extra m' delays when performing the Wald tests. It is only there to fix the asymptotic;
- Step 9 = The Wald test statistics will be asymptotically chi-square distributed with p′ df., Below the null value;
- Step 10 = Rejection of the null hypothesis implies a rejection of Granger's non-causality. That is, a refusal supports the presence of Granger's causality[19].

[19] See Granger, C. W. J. (1969).

A variable "x" causes a variable "y" if, the past values of "y" and the past values of "x" are useful for predicting future values of "y". A common method to test Granger's causality is to regress "y" on its delayed values and the "x" delayed values and test the null hypothesis that the coefficients estimated on the delayed values of "x" are jointly zero. Failure to reject the null hypothesis is equivalent to the non-refusal of the hypothesis that "x" does not cause "y".

For each equation and each endogenous variable that is not the dependent variable, if the test does not return the estimate of the coefficients on all the delays jointly equal to "0", then the variables are not characterized by Granger causality[20].

20 See Amisano, G., and Giannini C. (1997).

4.3 Results and Comments

The statistical test of Toda and Yamamoto (1995) was used to measure whether Granger causality exists among the time series of the variables of the available Bloomberg dataset. For the purpose of the correct functioning of the test, the average of the forecasts and revisions issued by each predictor for each quarter of the horizon considered was calculated. Therefore, each predictor could have up to a maximum of 38 average forecasts in the period from 2007 to the second quarter of 2016 (38 average forecasts out of 38 available quarters).

The first application of the Toda and Yamamoto test (1995) was carried out on the historical series of all the intermediaries who, in the time horizon indicated above, had issued 100% of the average forecasts (38 average forecasts out of 38 available quarters). The results of applying the test to the 26 financial institutions with 100% average forecasts in the 38 quarters available showed that there is no Granger causality (see the table in Appendix A.5). This result allows us to say that there is no leader in the euro-dollar exchange rate market among the 26 predictors considered.

The second application to the available data, after having tested Granger's non-causality among the historical series of the 26 variables that issued 38 average forecasts on 38 available quarters, was carried out on the top five banks in the world, according to the ranking "The World's 10 largest banks by total assets (2007) ", shown in Table 12. The idea is to understand whether there is Granger causality between Barclays, BNP Paribas, Credit Agricole, Deutsche Bank and Royal Bank of Scotland (which have the historical series and which represent the

“Top 5” banks based on the value of the asset recorded in 2007) and all the other banks available in the dataset. In order for the test to function correctly, the average forecasts of the top five banks and that of all the remaining banks of the dataset were calculated and indicated with the name of "The others".

Table 12 - The World's 10 largest banks by total assets (2007)[21]

Rank	Company	Country	Assest*
1	Royal Bank of Scotland	UK	3.783
2	Deutsche Bank	Germany	2.954
3	BNP Paribas	France	2.477
4	Barclays	UK	2.443
5	Credit Agricole	France	2.068
6	UBS	Switzerland	2.007
7	Societe Generale	France	1.567
8	ABN AMRO	Netherlands	1.499
9	ING Bank	Netherlands	1.453
10	The Bank of Tokyo-Mitsubishi UFJ	Japan	1.363

*USD(trillion)

This Table shows the list of the 10 largest banks in the World by total assets (2007), which includes any material or immaterial value of the company, which can be directly or indirectly hedged against liabilities. The values listed in the table are expressed in trillions of US dollars.

Table 13 - Wald test “Top 5” banks by assets vs “The others”

Equation	Excluded	chi2	df	Prob>chi2
Top 5	The others	10.271	1	0.001
Top5	ALL	10.271	1	0.001
The others	Top 5	0.00041	1	0.984
The others	ALL	0.00041	1	0.984

This Table shows the application of the Toda Yamamoto test (1995), through the use of the Wald function of the Stata software. The test was conducted on the average of the forecasts of the Top 10 banks based on the ranking reported in Table 12 and shows that Granger causality exists between the forecasts of the top 5 banks and the forecasts of all the other banks available in the Bloomberg dataset.

The results of the application of the Toda and Yamamoto test (1995), reported in Table 13, show that Granger causality exists between the top five assets banks and the rest of the banks available in the Bloomberg dataset. This means that the delayed values of the "Top 5" can

[21] Fonte: https://banksdaily.com/topbanks/World/2007.html

predict "The others", therefore the "Top 5" cause "The others". However, the same thing does not happen for "The others", which do not cause the "Top 5". Therefore, we can accept the null hypothesis at a 5% significance level. This result suggests that the direction of causality goes from the "Top 5" banks to "The others" banks.

After successfully testing the Granger causality among the "Top 5" banks by assets (2007), it was decided to extend the test to the top 10 banks of the same ranking, analysing whether there is a cause and effect relationship among the average of the average forecasts of the top 10 banks (according to the 2007 assets classification) and all the other banks available in the dataset. The results of the Toda and Yamamoto test (1995) reported in Table 14, show that Granger causality does not exist among the 10 most important banks in the world (according to the 2007 asset ranking) and all the remaining banks available in the dataset. This means that the delayed values of the "Top 10" cannot predict "The others", therefore the "Top 10" do not cause "The others". The same thing happens for "The others", which do not cause the "Top 5". The results, reported in Table 14, do not allow to affirm the presence of Granger causality, since for any dependent variable, the value of the coefficient of the endogenous variables is jointly major than, or equal to "0.05" (Prob> chi2). It follows that we cannot reject the null hypothesis at a significance level of 5%, since the average forecasts of the "Top 5" and "The others" banks are not characterized by Granger causality in the horizon considered.

Table 14 - Wald test "Top 10" banks by assets vs “The others”

Equation	Excluded	chi2	df	Prob>chi2
Top 10	The others	0.87066	1	0.351
Top 10	ALL	0.87066	1	0.351
The others	Top 10	0.66651	1	0.414
The others	ALL	0.66651	1	0.414

This Table shows the application of the Toda Yamamoto test (1995), through the use of the Wald function of the Stata software. The test was conducted on the average of the forecasts of the Top 10 banks based on the ranking reported in Table 12 and shows that no Granger causality exists between the forecasts of the top 10 banks and the forecasts of all the other banks available in the Bloomberg dataset.

In order to further analyse the degree of cause and effect that binds the banks in question, it was decided to measure whether there is an undisputed market leader, to which all the others adapt. The results, however, do not show this hypothesis. Therefore, the five most important banks according to the classification of assets (2007) (see Table 12), issue forecasts systematically in advance of all the others (see Table 13), but among them there is not a single undisputed leader in the euro-dollar exchange rate market, which takes precedence over all the others, as shown in Table 15.

Table 15 - Wald test between Top 5 assets banks (2007)

Equation	Excluded	chi2	df	Prob>chi2
Royal Bank of Scotland	Deutsche Bank	.1152	1	0.734
Royal Bank of Scotland	BNP Paribas	9.6642	1	0.002
Royal Bank of Scotland	Barclays	3.9639	1	0.046
Royal Bank of Scotland	Credit Agricole	.91986	1	0.338
Royal Bank of Scotland	ALL	22.659	4	0.000
Deutsche Bank	Royal Bank of Scotland	0.14412	1	0.704
Deutsche Bank	BNP Paribas	0.04057	1	0.840
Deutsche Bank	Barclays	7.3832	1	0.007
Deutsche Bank	Credit Agricole	17.346	1	0.000
Deutsche Bank	ALL	29.827	4	0.000
BNP Paribas	Royal Bank of Scotland	0.7596	1	0.383
BNP Paribas	Deutsche Bank	0.12763	1	0.721
BNP Paribas	Barclays	0.82947	1	0.362
BNP Paribas	Credit Agricole	0.39982	1	0.527
BNP Paribas	ALL	3.305	4	0.508
Barclays	Royal Bank of Scotland	1.5872	1	0.208
Barclays	Deutsche Bank	0.04182	1	0.838
Barclays	BNP Paribas	0.0884	1	0.766
Barclays	Credit Agricole	0.01219	1	0.912
Barclays	ALL	3.5414	4	0.472
Credit Agricole	Royal Bank of Scotland	1.0348	1	0.309
Credit Agricole	Deutsche Bank	0.24723	1	0.619
Credit Agricole	BNP Paribas	2.1637	1	0.141
Credit Agricole	Barclays	8.857	1	0.003
Credit Agricole	ALL	10.899	4	0.028

This Table shows the application of the Toda Yamamoto test (1995), through the use of the Wald function of the Stata software. The test was conducted on the average of the forecasts issued by each Top 5 World banks for total assets and shows that no Granger causality exists between the forecasts of the top 5 banks.

The results do not allow to affirm the presence of Granger causality, since for any dependent variable, the value of the coefficient of the endogenous variables is jointly major than, or equal to "0.05" (Prob> chi2). It follows that we cannot reject the null hypothesis at a significance level of 5%, since the average forecasts of the "Top 5" banks are not characterized by Granger causality in the horizon considered, which runs from 2007 to the second quarter of 2016. This means for example, that if we consider two variables X and Y, the delayed values of X and Y cannot predict X, so Y does not cause X. And the same happens X, which does not cause Y. In the test applied through the Stata software, the causality occurs only if regressing Y to its own delayed values and to the delayed values of X, and testing the null hypothesis that the coefficients estimated on the delayed values of X are jointly zero. Failure to reject the null hypothesis is equivalent to not rejecting the hypothesis that X does not cause Y.

Table 16 - The World's 20 largest banks by total equity (2007) [22]

Rank	Company	Equity*
1	Bank Of America	135.271
2	Citigroup Inc.	119.783
3	JP Morgan Chase	115.790
4	HSBC	114.928
5	Mitsubishi UFJ Financial Group	81.940
6	Royal Bank Of Scotland Group	78.730
7	ING Group	78.088
8	Credit Agricole	77.462
9	Wachovia Corporation	69.716
10	BNP Paribas	67.378
11	Banco Santander	62.072
12	Industrial and Commercial Bank of China	58.975
13	Barclays Plc	53.050
14	Unicredit Group	50.726
15	Wells Fargo	45.814
16	Deutsche Bank AG	44.142
17	Bank Of China Limited	44.137
18	China Construction Bank	42.294
19	Mizuho Financial Group	40.724
20	UBS AG	40.703

*USD(billion)

This table shows the list of the 20 largest banks in the World by total equity (2007), that is, the value at which each share would be redeemed if the company were closed and the assets sold. The values listed in the table are expressed in billion US dollars.

The third application of the test was made on the first five banks according to the ranking "The World's 20 largest banks by total equity (2007)" shown in Table 16. The procedure with which the test was carried out is the same as above. The average of the forecasts issued by the

[22] Fonte: https://banksdaily.com/topbanks/World/2007.html

top five banks by equity was calculated, in the horizon from 2007 to the second quarter of 2016. Then the same operation was carried out for the average of the forecasts issued by the other available banks, through which we generated the variable "The others". Furthermore, in this case the goal was to demonstrate the existence of Granger causality among the top five banks in the world according to the world ranking based on the value of equity in 2007 and the remaining banks of the Bloomberg dataset available.

The results of the application of the Toda and Yamamoto test (1995), reported in Table 17, between the top five equity banks and the rest of the banks available in the Bloomberg dataset, show that Granger causality exists. This means that the delayed values of the "Top 5" can predict "The others", therefore the "Top 5" cause "The others". However, the same thing does not happen for "The others", which do not cause the "Top 5". Therefore, we can accept the null hypothesis at a 5% significance level. This result suggests that the direction of causality goes from the "Top 5" banks to "The others" banks.

Table 17 - Wald test “Top 5” banks by equity vs “The others”

Equation	Excluded	chi2	df	Prob>chi2
Top 5	The others	12.688	1	0.000
Top 5	ALL	12.688	1	0.000
The others	Top 5	3.2403	1	0.072
The others	ALL	3.2403	1	0.072

This Table shows the application of the Toda Yamamoto test (1995), through the use of the Wald function of the Stata software. The test was conducted on the average of the forecasts of the Top 20 banks based on the ranking reported in Table 16 and shows that Granger causality exists between the forecasts of the top 5 banks and the forecasts of all the other banks available in the Bloomberg dataset.

After successfully testing the Granger causality among the "Top 5" banks by equity (2007), it was decided to extend the test to the top 10 banks of the same ranking, analysing whether a cause and effect relationship exists among the average of the average forecasts of the top 10 banks (according to the 2007 equity ranking) and all the other banks available in the dataset. The results of the Toda and Yamamoto test (1995) reported in Table 18 show that Granger causality exists among the 10 most important banks in the world (according to the equity ranking of 2007) and all the remaining banks available in the dataset. This means that the delayed values of the "Top 10" can predict "The others", therefore the "Top 10" cause "The others". The same thing happens for "The others", which cause the "Top 5". The direction of causality goes from the "Top 10" banks, to "The others" banks and vice versa. Therefore, we can accept the null hypothesis at a 5% significance level, because, since for any dependent variable, the value of the coefficient of the endogenous variables is jointly less than, or equal to "0.05" (Prob> chi2).

Table 18 - Wald test "Top 10" banks by equity vs “The others”

Equation	Excluded	chi2	df	Prob>chi2
Top 10	The others	7.0398	1	0.008
Top 10	ALL	7.0398	1	0.008
The others	Top 10	3.7735	1	0.052
The others	ALL	3.7735	1	0.052

This table shows the application of the Toda Yamamoto test (1995), through the use of the Wald function of the Stata software. The test was conducted on the average of the forecasts of the top 20 banks based on the ranking shown in table 16 and shows that Granger causality exists between the forecasts of the top 10 banks and the forecasts of all the other banks available in the Bloomberg dataset.

In order to further analyse the degree of cause and effect that binds the banks in question, it has been measured as before whether there is an undisputed market leader, to which all the others adapt. However, the results do not show this hypothesis. Therefore, the five most important banks according to the equity ranking (2007) (see Table 16), systematically issue forecasts in advance of all the others (see Table 17), but among them there is not a single undisputed leader, of the exchange rate market in euro-dollar currency, which takes over all the others, as shown in Table 19.

Table 19 - Wald test between Top 5 equity banks (2007)

Equation	Excluded	chi2	df	Prob>chi2
JPMorgan Chase	HSBC Holdings	31.181	1	0.000
JPMorgan Chase	Bank of America	0.80478	1	0.370
JPMorgan Chase	MUFG	12.252	1	0.000
JPMorgan Chase	Citigroup	1.336	1	0.248
JPMorgan Chase	ALL	106.51	4	0.000
HSBC Holdings	JPMorgan Chase	2.3076	1	0.129
HSBC Holdings	Bank of America	0.0099	1	0.921
HSBC Holdings	Mitsubishi UFJ Financial Group	0.93115	1	0.335
HSBC Holdings	Citigroup	1.1109	1	0.292
HSBC Holdings	ALL	9.8309	4	0.043
Bank of America	JPMorgan Chase	0.05161	1	0.820
Bank of America	HSBC Holdings	17.819	1	0.000
Bank of America	Mitsubishi UFJ Financial Group	5.806	1	0.016
Bank of America	Citigroup	6.475	1	0.011
Bank of America	ALL	27.164	4	0.000
Mitsubishi UFJ Financial Group	JPMorgan Chase	25.007	1	0.000
Mitsubishi UFJ Financial Group	HSBC Holdings	0.19783	1	0.656
Mitsubishi UFJ Financial Group	Bank of America	0.01597	1	0.899
Mitsubishi UFJ Financial Group	Citigroup	0.25495	1	0.614
Mitsubishi UFJ Financial Group	ALL	31.949	4	0.000
Citigroup	JPMorgan Chase	0.46933	1	0.493
Citigroup	HSBC Holdings	1.4389	1	0.230
Citigroup	Bank of America	0.28474	1	0.594
Citigroup	Mitsubishi UFJ Financial Group	2.5934	1	0.107
Citigroup	ALL	4.556	4	0.336

This Table shows the application of the Toda Yamamoto test (1995), through the use of the Wald function of the Stata software. The test was conducted on the average of the forecasts issued by each Top 5 World banks for total equity and shows that no Granger causality exists between the forecasts of the top 5 banks

The results do not allow to affirm the presence of Granger causality, since for any dependent variable, the value of the coefficient of the endogenous variables is jointly major than, or equal to "0.05" (Prob> chi2). It follows that we cannot reject the null hypothesis at a significance level of 5%, since, the average forecasts of the "Top 5" banks are not characterized by Granger causality in the horizon considered, which runs from 2007 to the second quarter of 2016. This means that for example, if we consider two variables X and Y, the delayed values of X and Y cannot predict X, so Y does not cause X. And the same happens X, which does not cause Y. In the test applied through the Stata software the causality occurs only if regressing Y to its own delayed values and to the delayed values of X and testing the null hypothesis that the coefficients estimated on the delayed values of X are jointly zero. Failure to reject the null hypothesis is equivalent to not rejecting the hypothesis that X does not cause Y.

Finally, the last application of the Toda and Yamamoto test (1995) on the Bloomberg dataset available, took into consideration only the first bank according to the World's 20 largest banks by total equity (2007) ranking, which is the Bank of America Corporation (see Table 16), and the first bank according to the ranking of the World's 10 largest banks by total assets (2007), the Royal Bank of Scotland Group (see Table 12).

Table 20 - Wald test Bank of America vs Royal Bank of Scotland

Equation	Excluded	chi2	df	Prob>chi2
Royal Bank of Scotland	Bank of America	4.4995	1	0.034
Royal Bank of Scotland	ALL	4.4995	1	0.034
Bank of America	Royal Bank of Scotland	0.02387	1	0.877
Bank of America	ALL	0.02387	1	0.877

This Table shows the application of the Toda Yamamoto test (1995), through the use of the Wald function of the Stata software. The test was conducted on the average of the forecasts issued by the first bank according to the ranking of the Top 10 World banks by total assets, and by the first bank according to the ranking of the Top 20 World's banks by total equity, which are respectively the Royal Bank of Scotland and Bank of America Corporation. The test results show that Granger causality exists between the Royal Bank of Scotland and the Bank of America Corporation, but not vice versa.

The results shown in Table 20 demonstrate an interesting result, namely that the Royal Bank of Scotland Granger cause the Bank of America Corporation. Therefore, we can accept the null hypothesis at a 5% significance level. The results suggest that the direction of causality goes from the Royal Bank of Scotland to the Bank of America Corporation. This means that the delayed values of the Royal Bank of Scotland can predict the Bank of America

Corporation, therefore the Royal Bank of Scotland causes the Bank of America Corporation. However, the same thing does not happen for the Bank of America Corporation, that does not cause the Royal Bank of Scotland.

4.5 Conclusion

In conclusion, the results achieved through the application of the Toda and Yamamoto test (1995) have allowed us to demonstrate that there are indeed cause and effect links that characterize the forecasts of the exchange rates in euro-dollar currency of the banks analysed in the Bloomberg dataset available.

The outcome of our analysis is in line with the studies published by Andy Coghlan and Debora MacKenzie in the New Scientist magazine in 2011, that report the results achieved by a group of researchers from the Federal Institute of Technology in Zurich, Switzerland. Analysing the transnational relationships existing among 43,030 multinational companies, they have demonstrated the existence of 147 companies, mainly banks, called "super-entities", which collectively hold 40% of the total wealth of the entire transnational exchange network (see table Appendix A.6).

In addition, the results of the analyses carried out, further confirm the news of the maxi fine issued by the European Antitrust Authority to a group of banks, for having created a real "cartel" on the foreign exchange rate market. They demonstrate how Citigroup, JP Morgan, Mitsubishi UFJ Financial Group, Barclays and the Royal Bank of Scotland Group, already in

2007, according to our analyses, had established themselves as the leader of the exchange rate market, in euro-dollar currency, issuing forecasts that systematically "preceded" those of all other market predictors (see Tables 13, 17, 20). Furthermore, in our analyses we find that the Bank of America Corporation, HSBC Holdings, Deutsche Bank, BNP Paribas and Credit Agricole also act as market leaders (see Tables 17, 18).

Therefore, based on this discovery, the maxi fine imposed by the European Antitrust can be seen as the end of a supremacy that lasted for 12 years, and that has seen the aforementioned banks impose themselves in the market of exchange rates in euro currency, dollars and more. This operation, in fact, involved eleven currencies, including the British pound, the Yen, the Swiss franc, the Euro, the United States, Canadian, New Zealand and Australian dollar and the Danish, Swedish and Norwegian krone.

It follows that it would be interesting, as a further development of this chapter, to test whether in other currencies, through the test of Toda and Yamamoto (1995), in the same year, Granger causality results are obtained between Citigroup, JP Morgan, Mitsubishi UFJ Financial Group, Barclays and the Royal Bank of Scotland Group and the rest of the banks available in the Bloomberg dataset to which the analysis was subjected.

Appendix A. 5 - Granger causality Wald tests

Equation	Excluded	chi2	df	Prob>chi2
ANZ	ABA	5.1444	1	0.023
ANZ	AGS	3.8568	1	0.050
ANZ	BPN	7.6781	1	0.006
ANZ	BOA	0.96532	1	0.326
ANZ	CBA	9.1179	1	0.003
ANZ	CIB	3.1449	1	0.076
ANZ	COM	0.83913	1	0.360
ANZ	CSU	4.2613	1	0.039
ANZ	DNS	4.8094	1	0.028
ANZ	HSB	0.677	1	0.411
ANZ	ING	0.00149	1	0.969
ANZ	LBB	0.59168	1	0.442
ANZ	MPS	1.2015	1	0.273
ANZ	MS	5.988	1	0.014
ANZ	NAB	0.22808	1	0.633
ANZ	RAB	1.6367	1	0.201
ANZ	RBC	15.422	1	0.000
ANZ	RBS	10.304	1	0.001
ANZ	SAX	0.97741	1	0.323
ANZ	SCB	0.64227	1	0.423
ANZ	SCI	0.19526	1	0.659
ANZ	SEB	3.6611	1	0.056
ANZ	SG	2.3191	1	0.128
ANZ	TDS	0.27674	1	0.599
ANZ	WPC	0.00853	1	0.926
ANZ	ALL	456.32	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
ABA	AGS	5.1593	1	0.023
ABA	ANZ	1.1472	1	0.284
ABA	BPN	7.5495	1	0.006
ABA	BOA	1.6733	1	0.195
ABA	CBA	12.744	1	0.000
ABA	CIB	6.2566	1	0.012
ABA	COM	0.3513	1	0.355
ABA	CSU	3.89	1	0.003
ABA	DNS	0.991	1	0.319
ABA	HSB	0.05364	1	0.801
ABA	ING	0.38472	1	0.535
ABA	LBB	3.7739	1	0.052
ABA	MPS	0.64674	1	0.421
ABA	MS	15.008	1	0.000
ABA	NAB	0.19095	1	0.662
ABA	RAB	0.62026	1	0.431
ABA	RBC	15.493	1	0.000
ABA	RBS	6.1327	1	0.013
ABA	SAX	0.24151	1	0.623
ABA	SCB	2.5805	1	0.108
ABA	SCI	0.09312	1	0.760
ABA	SEB	15.344	1	0.000
ABA	SG	0.12657	1	0.722
ABA	TDS	2.3607	1	0.090
ABA	WPC	0.04499	1	0.832
ABA	ALL	333.88	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
AGS	ABA	0.29005	1	0.590
AGS	ANZ	2.2553	1	0.133
AGS	BPN	32.369	1	0.000
AGS	BOA	20.935	1	0.000
AGS	CBA	10.258	1	0.001
AGS	CIB	4.0631	1	0.044
AGS	COM	0.32741	1	0.567
AGS	CSU	20.851	1	0.000
AGS	DNS	1.1938	1	0.275
AGS	HSB	3.9776	1	0.046
AGS	ING	12.471	1	0.000
AGS	LBB	13.999	1	0.000
AGS	MPS	0.03904	1	0.843
AGS	MS	34.803	1	0.000
AGS	NAB	0.13981	1	0.708
AGS	RAB	5.9942	1	0.014
AGS	RBC	13.466	1	0.000
AGS	RBS	6.9619	1	0.008
AGS	SAX	3.5873	1	0.058
AGS	SCB	0.46525	1	0.495
AGS	SCI	2.919	1	0.088
AGS	SEB	7.431	1	0.006
AGS	SG	7.8688	1	0.005
AGS	TDS	0.00096	1	0.975
AGS	WPC	3.0635	1	0.080
AGS	ALL	539.14	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
BPN	ABA	0.51001	1	0.475
BPN	AGS	0.28517	1	0.593
BPN	ANZ	1.2042	1	0.272
BPN	BOA	2.5754	1	0.109
BPN	CBA	10.082	1	0.001
BPN	CIB	7.4146	1	0.006
BPN	COM	0.01463	1	0.904
BPN	CSU	1.702	1	0.000
BPN	DNS	0.24943	1	0.617
BPN	HSB	3.8709	1	0.049
BPN	ING	4.9563	1	0.026
BPN	LBB	24.897	1	0.000
BPN	MPS	2.1688	1	0.141
BPN	MS	19.779	1	0.000
BPN	NAB	2.215	1	0.137
BPN	RAB	1.6386	1	0.201
BPN	RBC	22.903	1	0.000
BPN	RBS	9.8511	1	0.002
BPN	SAX	0.04229	1	0.837
BPN	SCB	0.55648	1	0.456
BPN	SCI	1.772	1	0.183
BPN	SEB	29.145	1	0.000
BPN	SG	0.27192	1	0.602
BPN	TDS	0.15443	1	0.694
BPN	WPC	1.1535	1	0.283
BPN	ALL	736.3	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
BOA	ABA	7.4692	1	0.006
BOA	AGS	3.1503	1	0.076
BOA	ANZ	6.0711	1	0.014
BOA	BPN	19.513	1	0.000
BOA	CBA	11.971	1	0.001
BOA	CIB	0.58534	1	0.444
BOA	COM	0.9787	1	0.323
BOA	CSU	1.909	1	0.000
BOA	DNS	1.2123	1	0.271
BOA	HSB	0.23018	1	0.631
BOA	ING	2.3257	1	0.127
BOA	LBB	13.623	1	0.000
BOA	MPS	3.7595	1	0.053
BOA	MS	18.345	1	0.000
BOA	NAB	3.8877	1	0.049
BOA	RAB	0.05261	1	0.819
BOA	RBC	16.376	1	0.000
BOA	RBS	5.3773	1	0.020
BOA	SAX	2.5835	1	0.108
BOA	SCB	6.9881	1	0.008
BOA	SCI	0.2188	1	0.640
BOA	SEB	29.173	1	0.000
BOA	SG	2.2372	1	0.135
BOA	TDS	3.9994	1	0.046
BOA	WPC	1.0427	1	0.307
BOA	ALL	743.78	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
CBA	ABA	15.718	1	0.000
CBA	AGS	20.557	1	0.000
CBA	ANZ	2.4207	1	0.120
CBA	BPN	0.40093	1	0.527
CBA	BOA	0.84781	1	0.357
CBA	CIB	3.8483	1	0.050
CBA	COM	1.899	1	0.168
CBA	CSU	6.382	1	0.012
CBA	DNS	0.22556	1	0.635
CBA	HSB	0.56419	1	0.453
CBA	ING	0.03904	1	0.843
CBA	LBB	1.0801	1	0.299
CBA	MPS	0.84857	1	0.357
CBA	MS	1.8011	1	0.180
CBA	NAB	4.7468	1	0.029
CBA	RAB	2.5423	1	0.111
CBA	RBC	4.0447	1	0.044
CBA	RBS	7.5432	1	0.006
CBA	SAX	0.01075	1	0.917
CBA	SCB	2.1154	1	0.146
CBA	SCI	4.5105	1	0.034
CBA	SEB	3.475	1	0.062
CBA	SG	0.14104	1	0.707
CBA	TDS	0.39594	1	0.529
CBA	WPC	2.7019	1	0.100
CBA	ALL	1131.5	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
CIB	ABA	0.17333	1	0.677
CIB	AGS	3.0243	1	0.082
CIB	ANZ	0.03969	1	0.842
CIB	BPN	13.723	1	0.000
CIB	BOA	8.2107	1	0.004
CIB	CBA	7.1417	1	0.008
CIB	COM	0.03873	1	0.844
CIB	CSU	6.5589	1	0.010
CIB	DNS	1.4259	1	0.232
CIB	HSB	0.49655	1	0.481
CIB	ING	2.5051	1	0.113
CIB	LBB	2.7538	1	0.097
CIB	MPS	0.07391	1	0.786
CIB	MS	12.473	1	0.000
CIB	NAB	0.19491	1	0.659
CIB	RAB	1.5663	1	0.211
CIB	RBC	19.919	1	0.000
CIB	RBS	0.02097	1	0.885
CIB	SAX	1.1428	1	0.285
CIB	SCB	0.11002	1	0.740
CIB	SCI	2.5611	1	0.110
CIB	SEB	15.934	1	0.000
CIB	SG	10.095	1	0.001
CIB	TDS	0.08485	1	0.771
CIB	WPC	2.3658	1	0.124
CIB	ALL	337.94	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
COM	ABA	8.1473	1	0.004
COM	AGS	4.4172	1	0.036
COM	ANZ	0.3744	1	0.541
COM	BPN	7.905	1	0.005
COM	BOA	2.0029	1	0.157
COM	CBA	5.9166	1	0.015
COM	CIB	5.2865	1	0.021
COM	CSU	3.0482	1	0.081
COM	DNS	15.177	1	0.218
COM	HSB	0.53215	1	0.466
COM	ING	0.0351	1	0.851
COM	LBB	0.64494	1	0.422
COM	MPS	0.01418	1	0.905
COM	MS	15.331	1	0.000
COM	NAB	0.04859	1	0.826
COM	RAB	0.0454	1	0.831
COM	RBC	8.7745	1	0.003
COM	RBS	3.8675	1	0.049
COM	SAX	0.00341	1	0.953
COM	SCB	1.5612	1	0.211
COM	SCI	0.63212	1	0.427
COM	SEB	16.364	1	0.000
COM	SG	0.4858	1	0.486
COM	TDS	0.52821	1	0.467
COM	WPC	0.00374	1	0.951
COM	ALL	248.97	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
CSU	ABA	7.9492	1	0.005
CSU	AGS	6.0718	1	0.014
CSU	ANZ	1.7073	1	0.191
CSU	BPN	6.7331	1	0.009
CSU	BOA	1.786	1	0.181
CSU	CBA	8.1531	1	0.004
CSU	CIB	0.93883	1	0.333
CSU	COM	0.54947	1	0.459
CSU	DNS	1.528	1	0.216
CSU	HSB	1.3372	1	0.248
CSU	ING	0.59718	1	0.440
CSU	LBB	0.57933	1	0.447
CSU	MPS	0.07246	1	0.788
CSU	MS	13.541	1	0.000
CSU	NAB	0.66619	1	0.414
CSU	RAB	0.13031	1	0.718
CSU	RBC	3.8102	1	0.051
CSU	RBS	7.1682	1	0.007
CSU	SAX	1.9393	1	0.164
CSU	SCB	1.5859	1	0.208
CSU	SCI	0.65063	1	0.420
CSU	SEB	11.252	1	0.001
CSU	SG	3.2624	1	0.071
CSU	TDS	3.6917	1	0.055
CSU	WPC	0.03637	1	0.849
CSU	ALL	412.06	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
DNS	ABA	0.00296	1	0.957
DNS	AGS	1.4669	1	0.226
DNS	ANZ	0.21	1	0.647
DNS	BPN	2.8428	1	0.092
DNS	BOA	13.162	1	0.000
DNS	CBA	13.787	1	0.000
DNS	CIB	0.60644	1	0.436
DNS	COM	0.27887	1	0.597
DNS	CSU	11.395	1	0.001
DNS	HSB	4.7504	1	0.029
DNS	ING	8.1655	1	0.004
DNS	LBB	2.2728	1	0.132
DNS	MPS	0.36865	1	0.544
DNS	MS	10.968	1	0.001
DNS	NAB	0.15999	1	0.689
DNS	RAB	1.0627	1	0.303
DNS	RBC	11.812	1	0.001
DNS	RBS	0.00319	1	0.955
DNS	SAX	51.772	1	0.023
DNS	SCB	0.1867	1	0.666
DNS	SCI	0.25491	1	0.614
DNS	SEB	22.655	1	0.000
DNS	SG	8.5843	1	0.003
DNS	TDS	0.26423	1	0.607
DNS	WPC	2.7013	1	0.100
DNS	ALL	506.02	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
HSB	ABA	1.565	1	0.211
HSB	AGS	1.0568	1	0.304
HSB	ANZ	0.00139	1	0.970
HSB	BPN	21.857	1	0.000
HSB	BOA	12.429	1	0.000
HSB	CBA	4.1025	1	0.043
HSB	CIB	2.8833	1	0.090
HSB	COM	0.28424	1	0.594
HSB	CSU	17.406	1	0.000
HSB	DNS	0.16388	1	0.686
HSB	ING	9.4443	1	0.002
HSB	LBB	16.612	1	0.000
HSB	MPS	0.04838	1	0.826
HSB	MS	18.468	1	0.000
HSB	NAB	0.15295	1	0.696
HSB	RAB	8.9041	1	0.003
HSB	RBC	9.1232	1	0.003
HSB	RBS	0.07735	1	0.781
HSB	SAX	0.19254	1	0.661
HSB	SCB	0.20265	1	0.653
HSB	SCI	0.02461	1	0.875
HSB	SEB	6.9828	1	0.008
HSB	SG	0.74211	1	0.389
HSB	TDS	0.4239	1	0.515
HSB	WPC	8.3543	1	0.004
HSB	ALL	536.88	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
ING	ABA	5.0295	1	0.025
ING	AGS	4.2198	1	0.040
ING	ANZ	1.2506	1	0.263
ING	BPN	4.6417	1	0.031
ING	BOA	12.284	1	0.000
ING	CBA	38.62	1	0.000
ING	CIB	14.25	1	0.000
ING	COM	0.21349	1	0.644
ING	CSU	19.082	1	0.000
ING	DNS	0.62198	1	0.430
ING	HSB	1.7985	1	0.180
ING	LBB	8.894	1	0.003
ING	MPS	9.3734	1	0.002
ING	MS	29.659	1	0.000
ING	NAB	0.19134	1	0.662
ING	RAB	3.2235	1	0.073
ING	RBC	36.54	1	0.000
ING	RBS	11.399	1	0.001
ING	SAX	1.6659	1	0.197
ING	SCB	0.34604	1	0.556
ING	SCI	2.4131	1	0.120
ING	SEB	36.827	1	0.000
ING	SG	0.24424	1	0.621
ING	TDS	5.0145	1	0.025
ING	WPC	1.4994	1	0.221
ING	ALL	1083	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
LBB	ABA	8.9859	1	0.003
LBB	AGS	4.9468	1	0.026
LBB	ANZ	3.3517	1	0.067
LBB	BPN	17.786	1	0.000
LBB	BOA	0.79517	1	0.373
LBB	CBA	16.692	1	0.000
LBB	CIB	0.39422	1	0.530
LBB	COM	1.1392	1	0.286
LBB	CSU	25.577	1	0.000
LBB	DNS	0.17413	1	0.676
LBB	HSB	1.1619	1	0.281
LBB	ING	1.9048	1	0.168
LBB	MPS	0.26656	1	0.606
LBB	MS	26.361	1	0.000
LBB	NAB	1.9553	1	0.162
LBB	RAB	5.4432	1	0.020
LBB	RBC	15.021	1	0.000
LBB	RBS	6.1368	1	0.013
LBB	SAX	1.827	1	0.176
LBB	SCB	6.8427	1	0.009
LBB	SCI	0.91978	1	0.338
LBB	SEB	19.166	1	0.000
LBB	SG	0.10396	1	0.747
LBB	TDS	8.9739	1	0.003
LBB	WPC	2.7718	1	0.096
LBB	ALL	499.23	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
MPS	ABA	4.5584	1	0.033
MPS	AGS	1.5506	1	0.213
MPS	ANZ	0.22622	1	0.634
MPS	BPN	0.1637	1	0.686
MPS	BOA	0.84437	1	0.358
MPS	CBA	0.02792	1	0.867
MPS	CIB	1.939	1	0.164
MPS	COM	2.5641	1	0.109
MPS	CSU	12.666	1	0.000
MPS	DNS	0.221	1	0.638
MPS	HSB	0.70437	1	0.401
MPS	ING	0.00048	1	0.983
MPS	LBB	11.026	1	0.001
MPS	MS	0.22775	1	0.633
MPS	NAB	0.3678	1	0.544
MPS	RAB	2.5931	1	0.107
MPS	RBC	18.386	1	0.000
MPS	RBS	7.1418	1	0.008
MPS	SAX	3.098	1	0.078
MPS	SCB	6.1844	1	0.013
MPS	SCI	2.2753	1	0.131
MPS	SEB	17.561	1	0.000
MPS	SG	0.00117	1	0.973
MPS	TDS	1.2917	1	0.256
MPS	WPC	0.07382	1	0.786
MPS	ALL	624.81	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
MS	ABA	8.6387	1	0.003
MS	AGS	2.5281	1	0.112
MS	ANZ	3.8617	1	0.049
MS	BPN	2.9506	1	0.086
MS	BOA	0.24894	1	0.618
MS	CBA	9.2045	1	0.002
MS	CIB	5.5482	1	0.018
MS	COM	1.8746	1	0.171
MS	CSU	6.6783	1	0.010
MS	DNS	0.07125	1	0.790
MS	HSB	0.25134	1	0.616
MS	ING	4.3e+05	1	0.995
MS	LBB	6.1256	1	0.013
MS	MPS	0.33114	1	0.565
MS	NAB	0.33644	1	0.562
MS	RAB	0.64519	1	0.422
MS	RBC	6.4999	1	0.011
MS	RBS	8.6249	1	0.003
MS	SAX	0.64953	1	0.420
MS	SCB	1.2224	1	0.269
MS	SCI	0.53767	1	0.463
MS	SEB	8.8377	1	0.003
MS	SG	0.55907	1	0.455
MS	TDS	2.046	1	0.153
MS	WPC	0.91858	1	0.338
MS	ALL	447.88	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
NAB	ABA	0.47243	1	0.492
NAB	AGS	7.7142	1	0.005
NAB	ANZ	0.41814	1	0.518
NAB	BPN	5.2453	1	0.022
NAB	BOA	2.3227	1	0.127
NAB	CBA	8.3999	1	0.004
NAB	CIB	1.4061	1	0.236
NAB	COM	0.19744	1	0.657
NAB	CSU	5.8222	1	0.016
NAB	DNS	0.44857	1	0.503
NAB	HSB	0.03046	1	0.861
NAB	ING	0.26459	1	0.607
NAB	LBB	3.1625	1	0.075
NAB	MPS	0.11752	1	0.732
NAB	MS	12.638	1	0.000
NAB	RAB	0.46708	1	0.494
NAB	RBC	8.8529	1	0.003
NAB	RBS	0.87949	1	0.348
NAB	SAX	0.63643	1	0.425
NAB	SCB	0.96515	1	0.326
NAB	SCI	0.05181	1	0.820
NAB	SEB	11.24	1	0.001
NAB	SG	0.80876	1	0.368
NAB	TDS	0.04675	1	0.829
NAB	WPC	0.15467	1	0.694
NAB	ALL	315.27	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
RAB	ABA	6.4657	1	0.011
RAB	AGS	7.6373	1	0.006
RAB	ANZ	0.00592	1	0.939
RAB	BPN	3.9546	1	0.047
RAB	BOA	4.0286	1	0.045
RAB	CBA	11.847	1	0.001
RAB	CIB	3.5287	1	0.060
RAB	COM	0.08621	1	0.769
RAB	CSU	9.0988	1	0.003
RAB	DNS	2.5744	1	0.109
RAB	HSB	1.0556	1	0.304
RAB	ING	2.1846	1	0.139
RAB	LBB	0.95683	1	0.328
RAB	MPS	0.43205	1	0.511
RAB	MS	17.81	1	0.000
RAB	NAB	0.03725	1	0.847
RAB	RBC	10.223	1	0.001
RAB	RBS	7.2266	1	0.007
RAB	SAX	6.468	1	0.011
RAB	SCB	1.6368	1	0.201
RAB	SCI	0.03582	1	0.850
RAB	SEB	23.501	1	0.000
RAB	SG	0.97725	1	0.323
RAB	TDS	0.28443	1	0.594
RAB	WPC	0.00718	1	0.932
RAB	ALL	664.75	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
RBC	ABA	15.092	1	0.000
RBC	AGS	8.3845	1	0.004
RBC	ANZ	4.9229	1	0.027
RBC	BPN	20.005	1	0.000
RBC	BOA	3.2868	1	0.070
RBC	CBA	19.391	1	0.000
RBC	CIB	12.506	1	0.000
RBC	COM	6.976	1	0.008
RBC	CSU	9.2117	1	0.002
RBC	DNS	5.5069	1	0.019
RBC	HSB	0.28834	1	0.591
RBC	ING	0.6105	1	0.435
RBC	LBB	1.1476	1	0.284
RBC	MPS	0.1646	1	0.685
RBC	MS	18.072	1	0.000
RBC	NAB	0.00667	1	0.935
RBC	RAB	0.01904	1	0.890
RBC	RBS	3.3735	1	0.066
RBC	SAX	0.29075	1	0.590
RBC	SCB	0.92325	1	0.337
RBC	SCI	1.2598	1	0.262
RBC	SEB	31.172	1	0.000
RBC	SG	1.0019	1	0.317
RBC	TDS	0.00036	1	0.985
RBC	WPC	0.0096	1	0.922
RBC	ALL	534.78	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
RBS	ABA	1.7145	1	0.190
RBS	AGS	5.1296	1	0.024
RBS	ANZ	12.128	1	0.000
RBS	BPN	18.728	1	0.000
RBS	BOA	6.9777	1	0.008
RBS	CBA	27.993	1	0.000
RBS	CIB	8.9798	1	0.003
RBS	COM	1.2607	1	0.262
RBS	CSU	21.494	1	0.000
RBS	DNS	6.2014	1	0.013
RBS	HSB	1.9412	1	0.164
RBS	ING	3.0218	1	0.082
RBS	LBB	7.7207	1	0.005
RBS	MPS	5.6776	1	0.017
RBS	MS	18.837	1	0.000
RBS	NAB	6.2844	1	0.012
RBS	RAB	0.05111	1	0.821
RBS	RBC	37.407	1	0.000
RBS	SAX	1.7367	1	0.188
RBS	SCB	1.632	1	0.201
RBS	SCI	0.05364	1	0.817
RBS	SEB	38.713	1	0.000
RBS	SG	8.9023	1	0.003
RBS	TDS	5.003	1	0.025
RBS	WPC	0.46973	1	0.493
RBS	ALL	1039	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
SAX	ABA	16.081	1	0.000
SAX	AGS	12.446	1	0.000
SAX	ANZ	5.7977	1	0.016
SAX	BPN	29.375	1	0.000
SAX	BOA	2.2502	1	0.134
SAX	CBA	15.788	1	0.000
SAX	CIB	8.0988	1	0.004
SAX	COM	1.7749	1	0.183
SAX	CSU	5.5086	1	0.019
SAX	DNS	1.003	1	0.317
SAX	HSB	11.168	1	0.001
SAX	ING	0.00812	1	0.928
SAX	LBB	6.1554	1	0.013
SAX	MPS	0.91101	1	0.340
SAX	MS	39.094	1	0.000
SAX	NAB	0.51903	1	0.471
SAX	RAB	0.00292	1	0.957
SAX	RBC	32.812	1	0.000
SAX	RBS	29.247	1	0.000
SAX	SCB	1.1543	1	0.283
SAX	SCI	0.02488	1	0.875
SAX	SEB	17.715	1	0.000
SAX	SG	0.84008	1	0.359
SAX	TDS	11.207	1	0.001
SAX	WPC	0.1003	1	0.751
SAX	ALL	566.28	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
SCB	ABA	12.89	1	0.000
SCB	AGS	1.8307	1	0.176
SCB	ANZ	6.5049	1	0.011
SCB	BPN	7.4648	1	0.006
SCB	BOA	0.01596	1	0.899
SCB	CBA	5.1463	1	0.023
SCB	CIB	0.74263	1	0.389
SCB	COM	4.6771	1	0.031
SCB	CSU	23.612	1	0.000
SCB	DNS	0.01792	1	0.894
SCB	HSB	4.72	1	0.030
SCB	ING	0.31949	1	0.572
SCB	LBB	11.584	1	0.001
SCB	MPS	0.14559	1	0.703
SCB	MS	11.39	1	0.001
SCB	NAB	1.7e+06	1	0.999
SCB	RAB	5.1473	1	0.023
SCB	RBC	12.875	1	0.000
SCB	RBS	6.236	1	0.013
SCB	SAX	2.5924	1	0.107
SCB	SCI	0.34529	1	0.557
SCB	SEB	15.58	1	0.000
SCB	SG	1.9446	1	0.163
SCB	TDS	6.8947	1	0.009
SCB	WPC	7.7	1	0.006
SCB	ALL	528.47	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
SCI	ABA	4.6638	1	0.031
SCI	AGS	3.5257	1	0.060
SCI	ANZ	11.39	1	0.001
SCI	BPN	5.279	1	0.022
SCI	BOA	7.9366	1	0.005
SCI	CBA	10.416	1	0.001
SCI	CIB	6.2114	1	0.013
SCI	COM	0.53964	1	0.463
SCI	CSU	11.892	1	0.001
SCI	DNS	1.6147	1	0.204
SCI	HSB	0.61423	1	0.433
SCI	ING	15.696	1	0.210
SCI	LBB	3.514	1	0.061
SCI	MPS	1.2421	1	0.265
SCI	MS	17.507	1	0.000
SCI	NAB	0.37935	1	0.538
SCI	RAB	0.75829	1	0.384
SCI	RBC	17.922	1	0.000
SCI	RBS	0.64416	1	0.422
SCI	SAX	1.182	1	0.277
SCI	SCB	1.2191	1	0.270
SCI	SEB	27.915	1	0.000
SCI	SG	2.6783	1	0.102
SCI	TDS	3.9343	1	0.047
SCI	WPC	4.6e+05	1	0.995
SCI	ALL	591.33	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
SEB	ABA	4.1023	1	0.043
SEB	AGS	1.9161	1	0.166
SEB	ANZ	0.01363	1	0.907
SEB	BPN	3.3773	1	0.066
SEB	BOA	2.5201	1	0.112
SEB	CBA	0.59479	1	0.441
SEB	CIB	0.27238	1	0.602
SEB	COM	0.08615	1	0.769
SEB	CSU	10.992	1	0.001
SEB	DNS	0.43609	1	0.509
SEB	HSB	1.9192	1	0.166
SEB	ING	2.0443	1	0.153
SEB	LBB	5.7002	1	0.017
SEB	MPS	0.11494	1	0.735
SEB	MS	12.369	1	0.000
SEB	NAB	2.3218	1	0.128
SEB	RAB	2.1446	1	0.143
SEB	RBC	12.158	1	0.000
SEB	RBS	5.7132	1	0.017
SEB	SAX	2.9366	1	0.087
SEB	SCB	0.86179	1	0.353
SEB	SCI	0.39859	1	0.528
SEB	SG	0.27749	1	0.598
SEB	TDS	0.00032	1	0.986
SEB	WPC	0.91115	1	0.340
SEB	ALL	323.75	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
SG	ABA	7.7949	1	0.005
SG	AGS	2.2872	1	0.130
SG	ANZ	13.424	1	0.000
SG	BPN	0.81719	1	0.366
SG	BOA	1.8477	1	0.174
SG	CBA	8.5474	1	0.003
SG	CIB	25.06	1	0.000
SG	COM	0.00415	1	0.949
SG	CSU	12.691	1	0.000
SG	DNS	0.16733	1	0.682
SG	HSB	0.13416	1	0.714
SG	ING	1.5339	1	0.216
SG	LBB	3.3396	1	0.068
SG	MPS	9.5566	1	0.002
SG	MS	16.342	1	0.000
SG	NAB	2.5e+06	1	0.999
SG	RAB	13.134	1	0.252
SG	RBC	22.148	1	0.000
SG	RBS	3.8651	1	0.049
SG	SAX	2.4165	1	0.120
SG	SCB	1.2591	1	0.262
SG	SCI	1.1229	1	0.289
SG	SEB	10.171	1	0.001
SG	TDS	9.8819	1	0.002
SG	WPC	2.2591	1	0.133
SG	ALL	889.12	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
TDS	ABA	9.8839	1	0.002
TDS	AGS	11.289	1	0.001
TDS	ANZ	9.8051	1	0.002
TDS	BPN	10.472	1	0.001
TDS	BOA	2.1081	1	0.147
TDS	CBA	5.7307	1	0.017
TDS	CIB	6.5856	1	0.010
TDS	COM	0.77079	1	0.380
TDS	CSU	3.6027	1	0.058
TDS	DNS	6.45	1	0.011
TDS	HSB	0.98098	1	0.322
TDS	ING	0.29777	1	0.585
TDS	LBB	4.0474	1	0.044
TDS	MPS	5.7394	1	0.017
TDS	MS	19.845	1	0.000
TDS	NAB	0.07046	1	0.791
TDS	RAB	0.078	1	0.780
TDS	RBC	5.7389	1	0.017
TDS	RBS	0.99727	1	0.318
TDS	SAX	7.921	1	0.005
TDS	SCB	0.46503	1	0.495
TDS	SCI	1.5964	1	0.206
TDS	SEB	1.5311	1	0.216
TDS	SG	2.4009	1	0.121
TDS	WPC	1.8486	1	0.174
TDS	ALL	691.35	25	0.000

Equation	Excluded	chi2	df	Prob>chi2
WPC	ABA	2.3015	1	0.129
WPC	AGS	11.124	1	0.001
WPC	ANZ	1.9626	1	0.161
WPC	BPN	4.3181	1	0.038
WPC	BOA	4.5879	1	0.032
WPC	CBA	13.564	1	0.000
WPC	CIB	1.4712	1	0.225
WPC	COM	0.10988	1	0.740
WPC	CSU	1.0672	1	0.302
WPC	DNS	2.1234	1	0.145
WPC	HSB	0.54668	1	0.460
WPC	ING	0.00426	1	0.948
WPC	LBB	0.50678	1	0.477
WPC	MPS	0.06351	1	0.801
WPC	MS	7.3625	1	0.007
WPC	NAB	0.13607	1	0.712
WPC	RAB	0.0257	1	0.873
WPC	RBC	10.006	1	0.002
WPC	RBS	0.8915	1	0.345
WPC	SAX	0.12338	1	0.725
WPC	SCB	0.11247	1	0.737
WPC	SCI	0.07493	1	0.784
WPC	SEB	22.715	1	0.000
WPC	SG	5.1959	1	0.023
WPC	TDS	1.8409	1	0.175
WPC	ALL	618.43	25	0.000

This table shows the application of the Toda Yamamoto test (1995), through the use of the Wald function of the Stata software. The test was conducted on the basis of the average of the forecasts issued by the 26 banks that in the Bloomberg dataset analysed, issued 100% of average forecasts (38 forecasts on 38 available quarters), in the horizon from the first quarter of 2007 to the second quarter of 2016. The results of the application of the Toda and Yamamoto test shows that there is no Granger causality between these variables.

Appendix A. 6 - The top 50 of the 147 “super-connected” companies

Bank name	Continent
1. Barclays plc	Europe
2. Capital Group Companies Inc	America
3. FMR Corporation	America
4. AXA	Europe
5. State Street Corporation	America
6. JP Morgan Chase & Co	America
7. Legal & General Group plc	Europe
8. Vanguard Group Inc	America
9. UBS AG	Europe
10. Merrill Lynch & Co Inc	America
11. Wellington Management Co LLP	America
12. Deutsche Bank AG	Europe
13. Franklin Resources Inc	America
14. Credit Suisse Group	Europe
15. Walton Enterprises LLC	America
16. Bank of New York Mellon Corp	America
17. Natixis	America
18. Goldman Sachs Group Inc	America
19. T Rowe Price Group Inc	America
20. Legg Mason Inc	America
21. Morgan Stanly	America
22. Mitsubishi UFI Financial Group Inc	Asia
23. Northern Trust Corporation	America
24. Société Générale	Europe
25. Bank of America Corporation	America
26. Lloyds TSB Group plc	Europe
27. Invesco plc	America
28. Allianz SE 29. TIAA	America
30. Old Mutual Public Limited Company	Africa
31. Aviva plc	Europe
32. Schroders plc	Europe
33. Dodge & cox	America
34. Lehman Brothers Holdings Inc	America
35. Sun Life Financial Inc	America
36. Standard Life plc	Europe
37. CNCE	Europe
38. Nomura Holdings Inc	Asia
39. The Depository Trust Company	America
40. Massachusetts Mutual Life Insurance	America
41. Ing Groep	Europe
42. Brandes Investment Partners LP	America
43. Unicredito Italiano SPA	Europe
44. Deposit Insurance Corporation of Japan	Asia
45. Vereniging Aegon	Europe
46. BNP Paribas	Europe
47. Affiliated Managers Group Inc	America
48. Resona Holdings Inc	Asia
49. Capital Group International Inc	America
50. China Petrochemical Group Company	Asia

This table shows the results achieved by a group of researchers from the Federal Institute of Technology in Zurich, Switzerland, who have demonstrated the existence of a group of "superentities" which alone would collectively hold 40% of the total wealth of the whole network of transnational exchanges. The study results were published by Andy Coghlan and Debora MacKenzie in New Scientist magazine in 2011.

CONCLUSION AND COMMENTS

Traditional neoclassical finance, which is based on the pillars of the theory of expected utility and efficient markets, reached its peak with the writings of Fama in 1970, according to which, markets are efficient, individuals are rational and have the sole objective of maximizing their usefulness, without any perception of the risk commensurate with it. However, this world view does not reflect reality. As will be shown shortly thereafter, individuals and the market are characterized by the presence of anomalous and irrational behaviours, which classical finance, with its traditional conception, cannot explain.

For this it was necessary to develop a new theoretical and empirical conception, which would fill these gaps. The rise of behavioural finance took place gradually, as there were numerous criticisms by neoclassical scholars, moving towards this new concept, which had as its objective to demonstrate that the theories promoted and published by scholars of the calibre of Fama (1970) were not completely realistic.

The theory behind behavioural finance is characterized by a strong empiric connotation, which arises from the application to the financial world of behavioural principles, coming from psychology, sociology and anthropology. For this reason, it can be defined as the science that studies the functioning of the markets through the behaviour of the operators who work in them, and the techniques from the human sciences, which allow us to have a more realistic view of the economic and financial world around us.

Sacha Gironde (2010) said that money has a particular effect on man, which contrasts strongly with the traditional conception, according to which it represents only a means to achieve an end. This is demonstrated by the fact that if an individual invests in the financial market generating a profit, the race to sell will take over., On the contrary, if the investment generates a loss of capital, it will tend to postpone the sale more than it should. This phenomenon occurs because we try to delay the sorrow for a loss as much as possible and, on the contrary, we try to anticipate the pleasure of a capital gain.

The purpose of the behavioural theory was to demonstrate that investors base their choices on a series of psychological paradigms, known as heuristics, which simplify the decision-making process underlying each investment choice. These "thought shortcuts" are very useful, but at the same time very dangerous, because they can generate cognitive errors or errors of judgment, pushing investors to make predictions about future events based exclusively on their perception of the available information and on their past experiences, believing that if an event has already happened, it cannot happen again or vice versa that it will certainly happen.

The typical example is that of roulette, which leads us to believe that if "red" comes out for 10 consecutive throws, "black" will certainly come out at the next throw and vice versa. But this is not correct, the probability at each throw is always 50/50.

To understand the decision-making process behind each investment choice made by an individual, behavioural theory was based on a series of purely psychological and social pillars, among which, the most important, is certainly the Prospect Theory, formulated by

Kahneman and Tversky in 1979. This theory takes into account the personal propensity of each individual to bear a certain risk commensurate with a certain loss (aversion), which is opposed to the theory of expected utility.

Richard Thaler (1993) said that behavioural finance is nothing but open-minded finance.

Therefore, behavioural theory will certainly not be able to make individuals rational, but it can certainly show us how the mistakes we make are not random, but, on the contrary, they are repeated, lasting and general, as we all make the same mistakes when speaking of money and investment.

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