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Tests of intraday trading rules for the FTSE-100 index

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ABSTRACT

The history of scientific research on the matter of the behavior of investors goes as far as the 16th century. However, most scrutiny and accomplishments occurred in the past century, and for most of that period the great debate has been centered on the question of market efficiency. The discussion has started in the 1960s and until this day there is still debate. Accordingly, in this study, I investigate if there is a technical trading rule, from a set of well-known trading rules, which can generate abnormal returns on the intraday data from the FTSE 100 Index from the period starting in January 2000 to December 2010. In other words, I try to attest for the validity of the weak form of the Efficient Market Hypothesis (EMH).

More precisely, I define and implement 5680 trading rules that use past information and test if they provide abnormal returns, testing the statistical significance of the results with the Superior Predictive Ability (SPA) test by Hansen (2005).

In that regard, the study allow to confirm the validity of the weak form of the EMH, since no tested rule can systematically outperform a buy and hold strategy. This result comes as no surprise considering the results achieve by similar studies, such as Marshall et al. (2008) Bajgrowicz and Scaillet (2012), Duvignage et al. (2013) and Chaboud et al. (2014).

These results contrast with other studies that also use trading rules with intraday data and refute the EMH. However their conclusions were not based on robust tests to data snooping.

In addition, further conclusions can be traced considering the duration and number of trades. The less time a portfolio is on the market for a given rule, the better is its performance. This can be indicative that the rules tested don’t generate value on their own merits, instead their results may simply be due to luck and to a small exposure to the market.

Key words: Technical analysis; Intraday data; Superior Predictive Ability test; Efficient Market Hypothesis.
RESUMO

O início da história do conhecimento científico relativo ao comportamento do investidor é datado ao século XVI. Contudo, somente no último século o assunto tem vindo a ser alvo de maior atenção, e na maior parte desse período tem-se debatido a questão da eficiência dos mercados. A discussão começou na década de 60 e ainda hoje se debate. Por consequência, neste estudo tento investigar a existência de uma técnica de transação de um conjunto de técnicas, pertencentes à análise técnica, de conhecimento prévio e bem documentadas na literatura, que consiga gerar rendibilidades anormais nos dados intradiários do índice FTSE 100, no período com início em Janeiro de 2000 e término em Dezembro de 2010.

Em detalhe, foram definidas e implementadas 5680 regras de transação que usam informação histórica, testando se geram rendibilidades anormais com o recurso ao teste SPA de Hansen (2005).


Esses resultados contrastam com outros estudos que também usaram regras de transação com dados intradiários e refutaram a teoria dos mercados eficientes. Contudo, essas conclusões não se fundamentaram em testes de robustez ao snooping dos dados. Adicionalmente, podem-se presumir ulteriores conclusões tendo em consideração a duração e o número de transações. Quanto menor o tempo de exposição do portfolio no mercado para uma determinada regra, melhor é a sua performance. Isto pode ser sinal de que as regras testadas não conseguem gerar valor por si só, pelo contrário, os seus resultados parecem ser obtidos de uma combinação de aleatoriedade e pouca exposição ao mercado.

Palavras-chave: Análise técnica; Base de dados intradiária; Teste Superior Predictive Ability; Teoria dos mercados eficientes.
## TABLE OF CONTENTS

ACKNOWLEDGMENTS ................................................................................................................................. III  

ABSTRACT ................................................................................................................................................... V  

RESUMO ................................................................................................................................................... VII  

TABLE OF CONTENTS ............................................................................................................................... IX  

LIST OF FIGURES ......................................................................................................................................... XI  

LIST OF TABLES ........................................................................................................................................ XIII  

LIST OF ACRONYMS AND ABBREVIATIONS ............................................................................................... XV  

CHAPTER 1 ................................................................................................................................................ 17  

1. INTRODUCTION ....................................................................................................................................... 17  

CHAPTER 2 ................................................................................................................................................ 19  

2. LITERATURE REVIEW ........................................................................................................................... 19  

   2.1. MODERN FINANCE, THE RANDOM WALK HYPOTHESIS AND EMH ............................................. 20  
   2.2. INTRADAY TECHNICAL ANALYSIS ................................................................................................. 23  
   2.3. DATA SNOOPING MEASURES ........................................................................................................... 28  

CHAPTER 3 ................................................................................................................................................ 31  

3. DATA ................................................................................................................................................... 31  

   3.1. SUMMARY ...................................................................................................................................... 31  
   3.2. DATA VERIFICATION ......................................................................................................................... 32  
   3.3. DATA AGGREGATION ......................................................................................................................... 34  
   3.4. RISK FREE RATE ............................................................................................................................... 34  

CHAPTER 4 ................................................................................................................................................ 35  

4. METHODOLOGY ...................................................................................................................................... 35  

   4.1. TECHNICAL TRADING RULES ......................................................................................................... 36  
   4.1.1. Filter rules .................................................................................................................................... 37  
   4.1.2. Moving averages ............................................................................................................................ 38  
   4.1.3. Support and resistance .................................................................................................................. 38  
   4.1.4. Channel breakouts ........................................................................................................................ 39  
   4.2. PERFORMANCE MEASUREMENT ................................................................................................. 40  
   4.3. DATA SNOOPING MEASURES .......................................................................................................... 40  

CHAPTER 5 ................................................................................................................................................ 43  

5. RESULTS AND ANALYSIS ..................................................................................................................... 43  

   5.1. RESULTS FOR THE AVERAGE RETURN CRITERION ................................................................... 43  
   5.1.1. Overview ..................................................................................................................................... 43  
   5.1.2. Duration of trades ......................................................................................................................... 50
5.1.3. Number of trades.......................................................................................................................... 53
5.1.4. Number of winning and losing trades........................................................................................ 56
5.1.5. Returns....................................................................................................................................... 59
5.2. SUPERIOR PREDICTIVE ABILITY TEST..................................................................................... 61

CHAPTER 6 ................................................................................................................................................ 63
6. CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORK .......................................................... 63
  6.1. CONCLUSIONS................................................................................................................................. 63
  6.2. SUGGESTIONS FOR FUTURE RESEARCH.................................................................................... 64

REFERENCES.............................................................................................................................................. 67

APPENDIX ................................................................................................................................................. 75
  APPENDIX 1 – OBSERVATIONS OUT OF CHRONOLOGICAL ORDER (ELIMINATED FROM THE DATASET). ......................... 75
  APPENDIX 2 – TRADING RULES PARAMETERS................................................................................... 76
    2.1. Filter rules ....................................................................................................................................... 76
    2.2. Moving averages.............................................................................................................................. 76
    2.3. Support and resistance .................................................................................................................... 77
    2.4. Channel Breakouts ......................................................................................................................... 77
LIST OF FIGURES

FIGURE 1 – FIRST DAILY OBSERVATION................................................................. 33
FIGURE 2 – LAST DAILY OBSERVATION................................................................. 34
FIGURE 3 – AVERAGE ANNUALIZED RETURN, BY YEAR (ANNUALIZED VALUES)............................................................. 46
FIGURE 4 – AVERAGE RETURN PER RULE, OVER THE ENTIRE PERIOD (2000 TO 2010), ANNUALIZED VALUES.................. 46
FIGURE 5 – AVERAGE EXCESS RETURN OVER THE BUY AND HOLD STRATEGY, BY YEAR (ANNUALIZED VALUES).................. 47
FIGURE 6 - AVERAGE EXCESS RETURN OVER THE BUY AND HOLD STRATEGY, FOR THE ENTIRE PERIOD (ANNUALIZED VALUES)...... 48
FIGURE 7 - AVERAGE EXCESS RETURN OVER THE RISK FREE RATE, BY YEAR. ........................................................................ 49
FIGURE 8 - AVERAGE EXCESS RETURN OVER THE RISK FREE RATE, FOR THE ENTIRE PERIOD................................................. 49
FIGURE 9 – MEAN DURATION OF TRADE BY YEAR, FOR THE FILTER RULES GROUP. ................................................................. 51
FIGURE 10 - MEAN DURATION OF TRADE BY YEAR, FOR THE MOVING AVERAGES GROUP. ...................................................... 51
FIGURE 11 – MEAN DURATION OF TRADE BY YEAR, FOR THE SUPPORT AND RESISTANCE GROUP. ........................................ 52
FIGURE 12 - MEAN DURATION OF TRADE BY YEAR, FOR THE CHANNEL BREAKOUTS GROUP. ..................................................... 52
FIGURE 13 - MEAN NUMBER OF TRades BY YEAR, FOR THE FILTER RULES GROUP. ................................................................. 54
FIGURE 14 - MEAN NUMBER OF TRades BY YEAR, FOR THE MOVING AVERAGES GROUP............................................................. 54
FIGURE 15 - MEAN NUMBER OF TRades BY YEAR, FOR THE SUPPORT AND RESISTANCE GROUP................................. 55
FIGURE 16 - MEAN NUMBER OF WINNING/LOSING TRades BY YEAR, FOR THE FILTER RULES GROUP. ........................................ 55
FIGURE 17 - MEAN NUMBER OF WINNING/LOSING TRades BY YEAR, FOR THE MOVING AVERAGES GROUP. ................................. 57
FIGURE 18 - MEAN NUMBER OF WINNING/LOSING TRades BY YEAR, FOR THE SUPPORT AND RESISTANCE GROUP. ............... 58
FIGURE 19 - MEAN NUMBER OF WINNING/LOSING TRades BY YEAR, FOR THE CHANNEL BREAKOUTS GROUP. ......................... 58
FIGURE 20 - MEAN NUMBER OF WINNING/LOSING TRades BY YEAR, FOR THE CHANNEL BREAKOUTS GROUP. ....................... 58
FIGURE 21 – MEAN RETURN BY YEAR, FOR THE FILTER RULES GROUP. ......................................................................................... 59
FIGURE 22 - MEAN RETURN BY YEAR, FOR THE MOVING AVERAGES GROUP................................................................. 60
FIGURE 23 - MEAN RETURN BY YEAR, FOR THE SUPPORT AND RESISTANCE GROUP. ................................................................. 60
FIGURE 24 - MEAN RETURN BY YEAR, FOR THE CHANNEL BREAKOUTS GROUP. ........................................................................ 61
LIST OF TABLES

TABLE 1 - DATABASE NUMBER OF OBSERVATIONS BY YEAR................................................................. 32
TABLE 2 - NUMBER OF TECHNICAL TRADING RULES USED............................................................ 36
TABLE 3 – AVERAGE PROPERTIES BY TRADING FAMILY, FOR THE ENTIRE PERIOD.......................... 45
TABLE 4 - COMPARISON OF THE AVERAGE TRADING DURATION FOR THE ENTIRE PERIOD, BY GROUP OF RULES............................................................ 53
TABLE 5 - SPA TEST RESULTS............................................................................................................ 62
LIST OF ACRONYMS AND ABREVIATIONS

CNBC - Consumer News and Business Chanel
DJIA – Dow Jones Industrial Average
EMH – Efficient Market Hypothesis
FIPS - Fixed Income Pricing System
FTSE 100 Index - Financial Times Stock Exchange 100 Index
FX - Foreign Exchange
GMT - Greenwich Mean Time
LSEG - London Stock Exchange Group
MIB30 - Milano Italia Borsa 30 Index
NASD - National Association of Securities Dealers
NASDAQ - National Association of Securities Automated Quotations
NYSE - New York Stock Exchange
S&P 500 – Standard and Poors 500
SPA test – Superior Predictive Ability test
SPDR – Standard and Poor’s Depository Receipts
UK - United Kingdom
USA – United States of America
CHAPTER 1

1. INTRODUCTION

For most of its life, the field of finance has debated the question of market efficiency. The discussion has started in the 1960s and until this day there is still debate, be it among academics or practitioners, about the question of markets efficiency. Among the scientific research on modern Finance those studies that are rated amongst the most influential on the matter are the 1953 Maurice Kendall’s study that brought to light the random movement of stock prices, coined as the random walk hypothesis (Kendall, 1953), and 1965 Eugene Fama’s work presenting, for the first time, the concept and definition of efficient markets. As he puts it, in an efficient market information is reflected on market prices, and thus prices should follow a random walk (Fama, 1965). Although this theory would later suffer some alterations by its own author (Fama, 1970, 1991), the underlying idea of the Efficient Market Hypothesis (EMH) is that a market is efficient if the prices fully reflect all available information.

Moreover, Fama defines the EMH in three forms, the weak form that implies that markets are efficient, reflecting all market historical information, the semi-strong form according to which the market is efficient reflecting all publicly available information, and finally the strong form that defines an efficient market in the sense that prices reflect all information both public and private (Fama, 1970).

Through the decades that followed these theories have been put under scrutiny, with several studies coming forward with contrary ideas. But in essence most of the academic world accepts the EMH and the random walk hypothesis.

The same cannot be said about practitioners, laying here the great discrepancy between the two sides of this area. Some market participants state that it is possible to predict the movements of the market just by taking into account the past prices and movements (technical analysis), which goes against the EMH.
For example, studies on the matter, such as Carter and Van Auken (1990), Allen and Taylor (1992), Lui and Mole (1998), and Oberlenchner (2001), consistently find that the practitioners emphasize technical analysis over fundamental analysis the shorter the time frame of forecasting. According to Marshall et al. (2008) practitioners place twice as much importance on technical analysis for intraday horizons when compared with a longer horizon of one year.

Consequently, it is only fitting that given the referred importance that practitioners deposit on technical trading, especially on short periods of time, and the abundance of studies, even those using intraday data, that find evidence for and against, the question of the profitability of the technical analysis, and thus the markets efficiency, remains current for both academics and market participants.

Accordingly, with this study, I investigate if there is a technical trading rule, from a set of well-known trading rules, which can generate abnormal returns on the Financial Times Stock Exchange (FTSE) 100 Index from the period starting in January 2000 to December 2010.

In order to accomplish those goals, from the several existing ways to test the weak form of the EMH, I define and implement trading rules that use past information and test if they provide abnormal returns (Lo et al., 2000; Jegadeesh, 2000).

Finally, in order to test the statistical significance of the results I use the Superior Predictive Ability test by Hansen (2005).
2. LITERATURE REVIEW

The knowledge about human behavior when one is faced with investment decisions has evolved substantially since Keynes’s *animal spirits* theory, resulting from the book entitled *The General Theory of Employment, Interest and Money* (Keynes, 1936). This theory conveys that the investor takes decisions based on random-like thinking, in such way that the stock market is comparable with a beauty contest. More precisely, Keynes says that “most, probably, of our decisions to do something positive, the full consequences of which will be drawn out over many days to come, can only be taken as a result of animal spirits, of a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of benefits multiplied by quantitative probabilities”.

In fact, this chapter follows with a review of the literature on the area which is subject to this study, intraday trading, more specifically the part dedicated to technical analysis. Since this is narrowly connected with the definition of the market efficiency and the random walk hypothesis I also present a small recap of the state of knowledge on the subject. Consequently I start by presenting a brief summary of the academic advances that led to, and followed, the formulation of the random walk hypothesis, and the EMH. More precisely, its origin, motivation, definition and the evolution on the literature about the subject, that presents strong arguments in favor and against it.

To end the chapter, I define and present statistical tests that account for data snooping used for studies in financial economics.
2.1. Modern Finance, the random walk hypothesis and EMH

The history of scientific research on the matter of the behavior of investors goes a long way back. According to Sewell (2011) it can be traced as far as the 16th century, when Girolamo Cardano, an Italian mathematician, wrote that “the most fundamental principle of all in gambling is simply equal conditions, e.g. of opponents, of bystanders, of money, of situation, of the dice box, and of the die itself. To the extent to which you depart from that equality, if it is in your opponents favor, you are a fool, and if in your own, you are unjust”. Since then the evolution of the scientific knowledge on the matter has been constantly evolving.

However, on the subject of the modern finance and more precisely the subject of technical analysis and the efficiency of the markets, most changes on the perception that we have about the role of the investor in the markets has occurred in the 1950s, 1960s and 1970s, fundamentally due to researchers such as Milton Friedman, Paul Samuelson, Maurice Kendall, Eugene Fama, Kenneth French, and Michael Jensen.

The most significant advances on this field started in 1953, when Milton Friedman pointed out that, due to arbitrage, the case for the EMH (which only latter would be presented and defined as we know it now) can be made even in situations where the trading strategies of investors are correlated (Friedman, 1953).

In the same year the first effort was made to make public the randomness of the movement of stock prices, by Maurice Kendall. He analyzed 22 price-series at weekly intervals and found that they were random (Kendall, 1953).

Later on, around 1955, it was credited to Louis Bachelier’s work on his PhD in mathematics from 1900, later published in book form entitled The Game, the Chance and the Hazard (translated from the original Le Jeu, la Chance et le Hasard) from 1914, a first insight on the theory presented in 1953 by Kendall (Bernstein, 1992).

Effectively, according to Bachelier, “past, present and even discounted future events are reflected in market price, but often show no apparent relation to price changes” and “if the market, in effect, does not predict its fluctuations, it does assess them as being more or less likely, and this likelihood can be evaluated mathematically” (Dimson and Mussavian, 2000).

Nevertheless, the first criticism to the random walk hypothesis did not take long to appear. In 1961, Houthakker resorted to stop-loss sell orders, finding patterns on the prices, and finding also leptokurtosis, nonstationarity and non-linearity (Houthakker, 1961).
In the year that followed, Mandelbrot suggested that the tails of the distribution of returns follow a power law (Mandelbrot, 1962). Cootner went as far as suggesting that the stock market do not follow a random walk (Cootner, 1962), and Osborne found out that stocks tend to be traded in concentrated bursts, which is a deviation from a simple random walk (Osborne, 1962).

For some of those criticisms there are possible explanations within the framework of the random walk hypothesis. For example, the model for error clustering by Berger and Mandelbrot (1963) serves as justification for the Mandelbrot’s critique in the previous year (Sewell, 2011), and the spectral analysis on market prices made by Granger and Morgenstern (1963) allowed them to conclude that short-run movements of the series obey the simple random walk hypothesis.

The situation described before persisted in the subsequent years, with the arrival of several studies in favor or against the random walk hypothesis and the EMH (Bernstein, 1992; Lo, 1997; Dimson and Mussavian, 1998; Farmer and Lo, 1999; Sewell, 2011).

The most prominent works in favor of such theories began with Eugene Fama’s discussion of Mandelbrot’s work in previous years, namely the stable paretian hypothesis, concluding that the tested market data conforms to the distribution (Fama, 1963). Godfrey et al. (1964) tested the random walk hypothesis on the stock market, concluding that it is the only mechanism that is consistent on describing the “unrestrained pursuit of the profit motive by the participants in the market”.

In the following year, Eugene Fama reviews previous studies and concludes that there is strong evidence in favor of the random walk hypothesis, presenting, for the first time, a definition of the concept of efficient markets (Fama, 1965).

Still in 1965, Paul Samuelson contributes for an extension on the perception of the markets efficiency, focusing on a martingale process instead of a random walk, and stating that “in competitive markets there is a buyer for every seller. If one could be sure that a price would rise, it would have already risen” (Samuelson, 1965).

This is followed by 1966 Mandelbrot’s work, where he concludes that in competitive markets with rational risk-neutral investors, returns are unpredictable, thus prices follow a martingale (Mandelbrot, 1966).

In 1967, Roberts introduces for the first time the distinction between weak and strong form of the market efficiency (Roberts, 1967). While Fama et al. (1969), considered the first ever event study, concluded that the stock markets are indeed efficient.
Fama (1970) defined an efficient market as a market where prices reflect all the available information, also making the distinction between weak form, semi-strong form and strong form of the EMH.

The decade that followed brought some other relevant studies, from which stand out Makiel (1973), Samuelson (1973), Grossman (1976), Fama (1976), and Jensen (1978). The last one introduced the distinction between the statistical and the economic efficiency. Jensen stated that a market is efficient with respect to a specific information set, if it is impossible to make economic profits by trading on the basis of that information set. Adding that “by economic profits, we mean the risk adjusted returns net of all costs” (Jensen, 1978).

In other words, Jensen intended to show that even if one can prove a market is inefficient by analyzing its prices, the same conclusion can be proved wrong when an investor tries to replicate the techniques and processes evaluated, since there are costs associated to each buy and sell operation. This is of most importance as most of studies relied on an approach that not accounted for costs and, mistakenly, draw conclusions against the EMH from the results obtained.


Even more recently, Bajgrowicz and Scaillet (2012) attest on favor of the markets efficiency. In this study the authors test the performance of technical trading rules on the Dow Jones Industrial Average (DJIA) index in the period from 1897 to 2011, using the false discovery rate (FDR), a new approach to data snooping, and proving wrong Brock et al. (1992), a similar study that used basically the same database and technical trading rules, but that led to different conclusions.

In the opposite side of the discussion there were also several studies trying to refute the random walk hypothesis as well as the EMH.

Indeed some of the most notable work, at an initial stage, was done by Sydney S. Alexander (Alexander, 1961, 1964), who concluded that the Standard and Poors (S&P) industrial index did not follow a random walk. Being followed by De Bondt and Thaler (1985), study where the authors discovered overreaction on the stock prices. This study is considered, by many, as the start of the behavioral finance research.
Additionally, Eugene Fama and Kenneth French find, in 1988, that 25 to 40 percent of the variation of long horizon returns is predictable from past returns (Fama and French, 1988). Whereas, Chan et al. (1996) found evidence that markets respond gradually to new information leading to periods of mispricing.

An extended number of other studies, also making the case against the EMH, accompanied these works.

In the decades of 1960 and 1970 the most notable works were accomplished by Steiger (1964), Granger and Morgenstern (1970), Kemp and Reid (1971), Beja (1977), and Ball (1978).


Even in the most recent years literature still emerges against the EMH (Wilson and Marashdeh, 2007; Lee et al., 2010).

This schism and continuous exchange of arguments is well summarized by Schwert in the article Anomalies and Market Efficiency, where he identifies the documented anomalies, finding that most of them disappeared, perhaps revealing some ephemeral market inefficiencies, finding also other new anomalies (Schwert, 2002).

2.2. Intraday technical analysis

Effectively one can conclude that this is an area of great debate and thus of great importance in Finance, be it for academics or practitioners.

In fact here lies the great discrepancy between the two sides of this area. In one hand we have the academics who, despite the divergences made clear above, always favored the idea that it is not possible to predict future price movements using the past price movements (technical analysis). In the other hand there are the market participants among whom there is the perception that it is possible to predict the movements of the market just by taking into account the past prices and movements.
The same statute of schism is not applicable to fundamental analysis. According to Lo et al. (2000), “it has been argued that the difference between fundamental analysis and technical analysis is not unlike the difference between astronomy and astrology”, complementing that “among some circles, technical analysis is known as “voodoo finance”.

Additionally, Lo et al. (2000) point out that the explanation behind this difference of treatment could be associated with the “unique and sometimes impenetrable jargon used by technical analysts”, adding that “some of which has developed into a standard lexicon that can be translated”. Be it as it may, the truth is that the discrepancy of treatment of the two approaches is very different depending if the subject is an academic or market participant.

The disposition of academics towards technical analysis, or charting as it is also referred, is well put by Makiel: “Technical analysis is anathema to the academic world. We love to pick on it. Our bullying tactics are prompt by two considerations: (1) the method is patently false; and (2) it is easy to pick on. And while it may seem a bit unfair to pick on such a sorry target, just remember: it is your money we are trying to save” (Makiel, 1981).

Regardless, studies on the matter, such as Carter and Van Auken (1990), Allen and Taylor (1992), Lui and Mole (1998), and Oberlenchner (2001), consistently find that the market participants emphasize technical analysis over fundamental analysis the shorter the time frame of forecasting. According to Marshall et al. (2008) they place twice as much importance on technical analysis for intraday horizons when compared with a longer horizon of one year.

This notion is a lot more relevant when authors such as Manahov et al. (2014) state that the discrepancy between academic studies related to technical trading, in the Foreign Exchange (FX) market, and practitioners is largely due to the fact that academic research limits their trading strategies to daily observations.

Having that in mind, the study of intraday technical analysis becomes of great importance on the matter of market efficiency.
To the best of my knowledge, the first study published using a higher trading frequency came up in 1985 entitled *An investigation of transactions data for NYSE stocks* by Wood et al. (1985). On it the authors tested a large sample of New York Stock Exchange (NYSE) stocks, examining them on a minute-by-minute transaction data period over two time periods, from September 1971 to February 1972 (data from 946 stocks) and the entire calendar year of 1982 (data from 1138 stocks). They found evidence of differences in return distributions among trades occurring overnight, during the first thirty minutes of trading day, at market close and during the rest of the day. Moreover, they realize that all positive returns are earned during the first thirty minute of the trading day and at the market close, and that in the rest of the day market returns are normally distributed and autocorrelation is substantially reduced (Wood et al., 1985).

Almost a decade later, Froot and Perold (1995) examine short-run autocorrelation of stock-index returns, finding that it has been declining dramatically in recent years. Over the period of 1983-1989 the returns on S&P 500 went from being highly positively correlated to practically uncorrelated. The paper shows that positive index autocorrelation found in earlier studies was a result of high autocorrelation on the 1960s and 1970s, vanishing by the late 1980s. The explanation for such is attributed to “inefficient processing of market-wide information”, pointing out “that recent technological and institutional improvements in the processing of this information has removed much of the autocorrelation”. In their study the authors used 15 minute returns, and they did not test for data mining.

Los (1999) tests and concludes that none of nine Asian currencies exhibited complete efficiency during the year of 1997. The author tested the stationarity and the serial independence of the price changes on minute-by-minute data for nine currencies during the period starting in January 1, 1997 to December, 30 1997, and, as Froot and Perold (1995), he did not conduct data snooping tests.
Already on the new millennium, Busse and Green (2002) examine the influence of live TV analysis on individual stocks during the trading day. In that regard they test 322 individual stocks featured on Morning Call and Midday Call of the network CNBC - Consumer News and Business Chanel (both programs are highly regarded by market participants). They use the simple mean of the intraday price changes and conduct the nonparametric bootstrap algorithm from Barclay and Litzenberger (1988) to determine the statistical significance. The conclusions to which they arrive are that in one hand the prices adjust within seconds of the initial mention, and in the other hand, traders who execute within 15 seconds of the initial mention make small but significant profits by trading on positive reports. In this study, the authors focus is not the market efficiency per se, rather the time of response from prices to news and big announcements. Even though, the fact that at a given period of time there are investors who can profit from stock prices, taking only into account past patterns (in this case a specific TV show indication and the market reaction to it), attests for market inefficiencies.

In the ensuing year, Hotchkiss and Ronen (2002) go on favor of the market efficiency, since they conclude that the bond market is quick to incorporate information, even at short return horizons. To get to that conclusion the authors used a dataset based on daily and hourly transactions for 55 high-yeld bonds included on the Fixed Income Pricing System (FIPS) from the National Association of Securities Dealers (NASD) between January 1995 and October 1995.

An opposite view is portrayed by Cassese and Guidolin (2004), once they examine the pricing and informational efficiency of the most important Italian stock index, the Milano Italia Borsa 30 (MIB30), in the period from April, 6 1999 to January, 31 2000. They found it quite inefficient, with a numerous percentage of the analyzed data (up to 40% of the data) violating non-arbitrage condition. Although, in order to reach to that conclusion, the authors did not account for transaction costs, they state that, even if transaction costs are considered, there are significant arbitrage opportunities.

Chordia et al. (2005) study the stocks listed on the NYSE from 1993 to 2002 and conclude that daily returns are not serially correlated while order imbalances on the same stocks are highly persistent. The authors add that this is due to the fact investors react promptly to order imbalances, taking 5 to 60 minutes in the process, also that short-term (5 minutes) return predictability has been declining and that market liquidity and efficiency are positively correlated. The authors did not conduct any significant test to control for data mining.
At their turn, Marshal et al. (2008) conclude that, for the Standard and Poor’s Depository Receipts (SPDR), intraday technical analysis is not profitable. The authors tested 7846 technical trading rules on data from 2002 and 2003, and controlled for data snooping through the application of the Brock et al. (1992) bootstrap methodology and the Sullivan et al. (1999) reality check test.

Chordia et al. (2008) perform a study on a sample of large and actively traded NYSE firms over a period of ten years (from 1993 to 2002) complemented later by Chung and Hrazdil (2010) on a broader study that included all NYSE traded firms. Both papers focus on the dynamics between liquidity and market efficiency, leading to the (same) conclusion that there is positive correlation between the two variables, being the effect amplified during periods of information release. In other words, according to both studies, liquidity enhances market efficiency.

A few years later, Scholstus and Dijk (2012) tried to find the relationship between the speed of trading and its performance. In order to accomplish it, the authors used data from S&P500, National Association of Securities Automated Quotations (NASDAQ) 100 and Russell 2000, from the period from January 6 of 2009 to September 30 of 2009. The study revealed that speed has an important role on the performance of the technical trading rules, being the ones with lower delays those with better (positive) average returns.

Other recent study that gave ground to the EMH was published in 2013. The authors tested the intraday predictive power using technical trading strategies on the 30 constituents of the DJIA index. They concluded that there is no abnormal return over the buy-and-hold strategy (Duvinage et al., 2013).

Furthermore, according to Chaboud et al. (2014), that focused on high frequency algorithmic trading on the FX, there is an improvement on price efficiency and a reduction on arbitrage opportunities associated primarily with automated (computer generated) trading.

Manahov et al. (2014) found evidence of statistical and economical significance of excess returns on the FX, even after accounting for the transaction costs. In this study, the authors did not conduct a robustness test on their results.

Indeed the existing literature on intraday technical analysis seems to be skewed on favor of the EMH and the random walk hypothesis, since most of studies point out that, after the consideration of transaction costs and data snooping measures, there are no trading strategies that can, consistently, beat the market, even considering trading strategies with shorter time frames.
Nonetheless, the fact that there is still some literature that try and succeed in finding flaws to the EMH and the *random walk hypothesis*, attest for the validity, even nowadays, of the question of the markets efficiency.

### 2.3. Data snooping measures

According to Leamer (1978) the empirical tests in financial economics which are free from data instigated biases are close to none. So in this kind of studies there is always the risk that the results are driven by data mining.

Following the same path, Lo et al. (1990) states that tests of financial asset pricing models may result in misleading inferences when properties of the data are used to construct the test statistics. Such tests are often based on returns to portfolios of common stock, where portfolios are constructed by sorting on some empirically motivated characteristic of the securities such as market value of equity.

Dimson and Marsh (1990) finds that “even apparently innocuous forms of data-snooping significantly enhance reported forecast quality, and that relatively sophisticated forecasting methods operated without data-snooping often perform worse than naive benchmarks”.

Moreover, Brock et al. (1992) adds that “the more scrutiny a collection of data receives, the more likely “interesting” spurious patterns will be observed”.

In order to illustrate the conundrum of data snooping, Bajgrowicz and Scaillet (2012) use a good anecdote. They state the following, “imagine you put enough monkeys on typewriters and that one of the monkeys writes *The Iliad* in ancient Greek. Because of the sheer size of the sample, you are likely to find a lucky monkey once in a while. Would you bet any money that he is going to write *The Odyssey* next?”.

The same argument can be applied to trading rules. If one looks hard enough, a trading rule will eventually generate abnormal returns, even if it lacks predictive ability.

Indeed, a good part of the literature evidence in favor of the predictive ability of technical trading rules can be draw back to studies made without accounting for data snooping biases. This is an issue that is transversal to most studies that were undertaken in the past, for both intraday and daily datasets.

Examples of this effect are Brock et al. (1992), Levich and Thomas (1993) and Osler and Chang (1999).

The possibilities to avoid such problems have been under greater discussion for the past 30 years, with special focus in the past decade.
In fact, Brock et al. (1992) presents a study where the authors conduct a test of significance for the set of technical trading rules employed, through the use of bootstrap. Diebold and Mariano (1995) produces a test intended to compare forecast, but actually has been largely used to compare models. However, Giacomini and White (2003) refers that this test is conservative when applied to short-horizon forecasts, since the model parameters are estimated using a rolling window of data, rather than an expanding one.

Other example of a well documented and widely used test is the reality check for data snooping (RC) of White (2000). The author created a test for comparing multiple forecasting models or rules. This procedure compares the total number of rules or models under estimation to a benchmark, and tests if the benchmark is significantly outperformed by any model used in that comparison.

This test would be refined by Hansen (2005), in the sense that it accounts for the variation of the outperformance of each model compared with the benchmark. This relative calculation results in a test less sensitive to the inclusion of poor and irrelevant alternatives.
3. DATA

For the purpose of the study, I used the intraday database on the FTSE 100 Index available on the School of Economics and Management, at the University of Minho. This database aggregates a total of 11 years of data, from January 2000 until December 2010, which, compared to the data commonly used on existing literature, is a considerable time frame, being, from a theoretical point of view, large enough to deliver robust results.

On the remainder of this chapter, I present a summary of the data on the database, some checks that were done in order to guarantee that there are no values mistakenly incorporated in the database, the aggregation of the data into lower frequencies, and, finally, the description of the risk free used.

3.1. Summary

The database has a total of 20,188,968 observations, distributed annually as showed on Table 1.

More precisely, from 2000 to 2008 there are about half a million observations each year, whereas in the last two years that number increases for more than 1.3 million in 2009, and more than 14 million in 2010. This happens because prior to December 2009 prices were made recorded on a 15 seconds interval (approximately), and from that date on prices entries were made with greater frequency (they were registered as changes occurred).
Table 1 - Database number of observations by year.

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>507,628</td>
</tr>
<tr>
<td>2001</td>
<td>463,828</td>
</tr>
<tr>
<td>2002</td>
<td>461,734</td>
</tr>
<tr>
<td>2003</td>
<td>471,774</td>
</tr>
<tr>
<td>2004</td>
<td>495,214</td>
</tr>
<tr>
<td>2005</td>
<td>495,707</td>
</tr>
<tr>
<td>2006</td>
<td>498,224</td>
</tr>
<tr>
<td>2007</td>
<td>455,235</td>
</tr>
<tr>
<td>2008</td>
<td>516,510</td>
</tr>
<tr>
<td>2009</td>
<td>1,331,934</td>
</tr>
<tr>
<td>2010</td>
<td>14,491,180</td>
</tr>
</tbody>
</table>

3.2. Data verification

According to the London Stock Exchange Group (LSEG) the trading hours for the FTSE 100 index starts at 08:00 and ends at 16:30 Greenwich Mean Time (GMT), except on the last working day preceding Christmas and New Year’s Eve, when it opens at 08:00 and closes at 12:30 GMT (London Stock Exchange Group - Official website of the London stock exchange, 2016).

Accordingly, the first and last daily observations on the database are presented on Figure 1 and on Figure 2, respectively.

Regarding the first daily observation, as expected, most of them occur precisely at 8 am. Even though, there are a few days where the first observation is not at 8 am or at an approximate time. In fact some days have the first entry from as late as 10 am. Besides that there are other values worthy of attention, exactly 3 prices which are registered past 12:00.

On the same premise, the last daily observation (represented on Figure 2) was also verified. Here, the observations are not in line with the first ones in each trading day. There a lot more discrepancies on the last recorded price.

For both cases, I conduct some verifications. I start by verifying if there are any reasons for those abnormal time stamps, and found that there are technical reasons for some of them. Then I proceed to compare the prices on the database to the prices on other database, namely the Thomson Reuters/Datastream database, and concluded that there are no major errors on the database and therefore decided to keep all records.
I also checked if there are any records outside trading days. In order to do that, I resorted to the institutional website of the United Kingdom (UK) government, obtaining the bank holidays on which it is not supposed to exist observations. After verification, no observations were found on weekends or holidays (UK Government. Official website of the UK government services and information, 2016). Furthermore, there are a few working days when there are no observations, for example the 9/11 terrorist attacks on the World Trade Center.

Next, I checked for the existence of observations off chronological order. Indeed there were 81 prices that entered off the correct chronological order. Those entries were eliminated from the dataset.

![Figure 1 – First daily observation.](image-url)
3.3. Data aggregation

When looking to Table 1 the main characteristic from the data that stands out is the different number of observations in the last two years compared to the previous ones. Such difference, as said before, is due to the change on the time frequency of the records of index values in the database. Since all trading rules considered assume that returns are calculated over the same time period, I aggregated returns to a five minute interval. The time frame of 5 minutes was chosen in accordance to other studies, such as Marshall et al. (2008).

3.4. Risk free rate

For the purpose of the analysis, the risk free rate used was obtained from the Thomson/Reuters database. The risk free rate here considered is the pound overnight middle rate provided by the Bank of England.
4. METHODOLOGY

In order to find if there is a technical trading rule that can generate abnormal, risk adjusted, returns, in other words, to test the weak form of the EMH, there are three common approaches. One is to find and test some kind of calendar regularity or anomaly; another form consists in analyzing the properties of the series (e.g. sample correlations, run tests, variance ratio tests); and yet another approach is to implement trading rules that use past information.

In fact, I use the later. In accordance, I define and implement trading rules that use past information and test if they provide abnormal returns (Lo et al., 2000; Jegadeesh, 2000). Effectively, the set of technical trading rules employed on the study were the ones purposed by several other studies, e.g. Sullivan et al. (1999), Marshall et al. (2008), Bajgrowicz and Scaillet (2012). Those techniques are known previously to the period of the data under analysis, hence avoiding data mining issues (Marshall et al., 2008).

Finally, for the test of profitability it is often used the Brock et al. (1992) bootstrapping methodology, the White’s Reality Check bootstrapping technique for data snooping (Sullivan et al., 1999, 2001, White, 2000), and the Superior Predictive Ability test (Hansen, 2005).

On this study I use the Superior Predictive Ability test (Hansen, 2005), from now on referred as SPA test, since it is more powerful and less sensitive to the inclusion of poor and irrelevant alternatives, when compared to the other approaches (Hansen, 2005).

Indeed, in the reminder of this chapter I present definitions for the technical trading rules employed, the measurements of performance and then, in more depth, the test to assess the statistical significance of the results.
4.1. Technical Trading Rules

Regarding the technical trading rules employed on this study, I looked for rules that were of common knowledge prior to the time frame of the data under analysis. This, according to Lakonishok and Smidt (1988), Lo and MacKinlay (1990), and Pesaran and Timmerman (1995), tends to avoid data snooping bias. This is well put by Marshall et al. (2008), “the application of new trading rules, or new specifications of existing trading rules, to historical data introduces the chance of data snooping bias. It is quite possible that the rules have been tailored to the data series in question and are only profitable because of this”.

Effectively, the rules employed were from four families of trading rules, filter rules, moving averages, support and resistance, and channel breakouts, used on several studies on the subject, such as Brock et al. (1992), Sullivan et al. (1999), Marshall et al. (2008) and Bajgrowicz & Scaillet (2012).

On Table 2 are presented the number of technical trading rules used on the study. A total of 5680 rules were tested, 600 of the filter rules, 3780 of the moving averages, 180 of the support and resistance and 1120 of the channel breakouts family.

<table>
<thead>
<tr>
<th>Family of trading rules</th>
<th>Number of rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>Filter rules</td>
<td>600</td>
</tr>
<tr>
<td>Moving averages</td>
<td>3780</td>
</tr>
<tr>
<td>Support and resistance</td>
<td>180</td>
</tr>
<tr>
<td>Channel breakouts</td>
<td>1120</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>5680</strong></td>
</tr>
</tbody>
</table>
4.1.1. Filter rules

In order to define and implement the trading rules from the filter rules family, first used by Alexander (1961), I resorted to Fama and Blume (1966) and to Sullivan et al. (1999). Both papers state that when a daily closing price of a security moves up or down at least $x$ per cent (being $x$ a value to be defined) one should buy and hold that security, or short sell, respectively. From there, each subsequent day, one should check the closing price, watching for two different possibilities, if the price goes down (or rises on the second scenario) for more than $x$ per cent the following action should be to sell (buy) the security, otherwise if the price goes up (down) it becomes the price of reference for it to be compared to the closing price in the next day, on all other price movements the position remains unchanged.

Since the database used is not composed of daily prices, but rather of intraday prices, the definitions cited for daily prices should be adapted accordingly. So the “closing price” is assumed as the last price prior to the current period under consideration.

Additionally to the standard filter rules described, there are some variations that I consider for this study.

Starting with the price of reference, which on the standard form is the subsequent high (low) if the position is long (short), it can be also defined as the most recent price that is greater (less) than the $e$ previous prices.

I also consider the possibility of a neutral position to be taken when the price decreases (increases) $y$ percent from the previous high (low). With $y$ less than $x$.

Finally, another variation to the standard filter is imposed by allowing a position to be held, be it long or short, for a given, $c$, number of periods, ignoring all other signals generated during that period.
4.1.2. Moving averages

Moving averages are among the groups of trading rules with wider use and discussion on technical trading literature. Its usage dates to the 30s, when Gartley (1935) mentioned that “in an uptrend, long commitments are retained as long as the price trend remains above the moving average. Thus, when the price trend reaches a top, and turns downward, the downside penetration of the moving average is regarded as a sell signal… Similarly, in a downtrend, short average. Thus, when the price trend reaches a bottom, and turns upward, the upside penetration of the moving average is regarded as a buy signal”.

Brock et al. (1992) stated that the idea behind this particular technique is to smooth out an otherwise volatile series.

Accordingly, a buy signal is generated when the short-period moving average rises above the long-term moving average, and vice-versa, when the short-period moving average falls below the long-period moving average a sell signal is generated. Therefore, the portfolio is always on the market, either with long or short positions.

As before, some variations of the standard moving averages were considered.

The first variation was introduced by applying a band filter on the moving average, which resulted on the reduction of the number of buy and sell signals by eliminating what Brock et al. (1992) describes as “whiplash” signals when the long and short period moving averages are close. In other words, the fixed percentage band filter requires the buy or sell signal to exceed the moving average by a fixed multiplicative amount, $b$.

The second variation considered was the time delay filter, which requires the buy or sell signal to be the same for a given number of periods, $d$. Only if a signal repeats itself for a number of periods equal to $d$, action is taken in order to act according to the signal.

The third and final variation is the same as the one used for the Filter Rules (on 4.1.1). A position is held for $c$ periods, ignoring all other signals during that period.

4.1.3. Support and resistance

Support and resistance is another group of technical trading rules with a well documented usage. According to Sullivan et al. (1999) it can be traced to Wyckoff (1910).
In its simplest form, a buy signal is generated when the price rises above the resistance level (local maximum). The logic behind this rule relies on the belief that many investors are willing to sell at a peak, leading to a potential selling pressure that causes resistance to the price penetration of the previous maximum. Though, if the price breaks through this pressure point and surpasses the resistance level, this should be perceived as a buy signal (Brock et al., 1992).

The same reasoning can be followed for sell signals. If the price drops below the support level (local minimum) a sell signal is generated.

As for the other groups of trading rules, I implemented some variations to the basic form defined above. Those were the same implemented for the moving averages, a fixed percentage band filter, \( b \), a time delay filter, \( d \), and position holding for \( c \) periods.

### 4.1.4. Channel breakouts

Sometimes referred to as the *Dow line* or *Dow Theory*, this technical trading rule has been around for more than a century. It was developed by Charles Dow, hence the titles coined to the rule, in the late years of the 19\(^{th}\) century.

The rule, later refined by William Hamilton (Hamilton, 1922) and better described by Robert Rhea (Rhea, 1932), states that one should buy when the closing price exceeds the channel and sell when the price moves below the channel. The channel occurs when the high over the previous \( n \) days is within \( x \) percent of the low over the previous \( n \) days, not including the current price (Sullivan et al., 1999).

Again, the previous definitions are specifically focused for daily prices. For this study some considerations are made resulting in the definition that follows: if the maximum price of the previous \( n \) periods is less or equal to \((1+x)\) times the minimum price of the same period, a channel occurs (1). Thus, and only after the previous condition is met, an evaluation is made to infer if the position to be held is long or short. The first occurs if the current price is higher than the maximum price of the previous \( n \) periods (2), the second when the opposite is verified (3).

\[
\text{Channel} : \max \ Pr \text{ice} \leq \min \ Pr \text{ice} \times (1 + x),
\]

Where \( \max \text{Price} \) is the highest price of the previous \( n \) periods, \( \min \text{Price} \) is the lowest price of the previous \( n \) periods.
Once again, variations of this basic form are considered. Namely, the fixed percent band filter, \(b\), and the fixed number of periods, \(c\), holding the same position.

### 4.2. Performance measurement

The results for the study were obtained following a simple algorithm, each trading rule generates an investment signal, 1, 0 or -1, respectively for a long, neutral and short position. According to Bajgrowicz and Scaillet (2012), other ways to manage the signals could be employed, but since the conclusion would be the same and this signals interpretation are fairly intuitive, I opted for this approach.

Regarding the performance measurement of those returns, I followed the relevant literature on the matter and used the risk free rate as benchmark (Sullivan et al., 1999 and on Brock et al., 1992), gauging if the rules are able to generate absolute returns. The risk free rates used are the overnight interest rates given by the Bank of England.

In detail, when the signal generated indicates to buy (1), I buy the index at the current price, if instead the signal is for a sell (-1), I go short on the index, and otherwise the portfolio is outside the market. For all that options, the portfolio is compared to the option of earning the risk free rate for the entire period.

Furthermore, as seen on Marshall et al. (2008), I use the index as a benchmark as well. This is accomplished by doing the same as for the risk free rate, although in this approach the comparison is made over a long position on the index for the whole period.

Finally, concerning the performance criteria, I use the simple mean return.

### 4.3. Data snooping measures

In order to avoid spurious patterns in the results I use the Superior Predictive Ability test by Hansen (2005). This consists in an evaluation of the trading rules in the context of the total group of rules, which reduces the significance of a rule if it is the only one presenting positive abnormal returns. In this case the null hypothesis is that the performance of the best trading rule is no better than the benchmark performance.
To be more specific, the SPA test checks if there is a trading rule with larger expected profit than the current rule.

Take $\delta_{k,t-1}$ (where $k = 0, 1, \ldots, m$) as the set of possible decision rules (long, short or neutral) at time $t-1$, which are evaluated with a loss function, $L(\xi, \delta_{t-h})$, where $\xi$ is a random variable that represents the aspects of the decision problem that are unknown at the time the decision is made. A given trading rule profit, $\pi_{k,t}$, is given by $\delta_{k,t-1}r_t$, where $r_t$ is the return on the asset in period $t$.

In this study the random variable, $\xi_t$, assumes the value of $r_t$, what makes the loss function, $L(\xi_t, \delta_{t-h})$, equal to the profit of the benchmark, $\delta_{k,t-1}r_t$ (long position on the index).

Given that, the performance, $d$, of the rule $k$, at time $t$, relative to the benchmark, is given by the following expression,

$$d_{k,t} = L(\xi_t, \delta_{k,t-1}) - L(\xi_t, \delta_{k,t-1}) , \quad k = 1,\ldots, m. \tag{4}$$

And the null hypothesis can then be as presented on (5), assuming an expected positive value for the performance of rule $k$ at time $t$.

$$H_0 = \mu \leq 0, \quad \text{with} \quad \mu \in \mathbb{R}^m \tag{5}$$

Furthermore, the test statistic is given by

$$T_{SPA}^{SPA} = \max \left[ \max_{k=1,\ldots,m} \left( \frac{n^{1/2}d_k}{\hat{\omega}_k^{1/2}} \right) , 0 \right] \tag{6}$$

Where $\hat{\omega}_k^{1/2}$ is some consistent estimator of $\omega_k^{1/2} = \text{var}(n^{1/2}d_k)$.

And the estimator is given by

$$\hat{\mu}_k^{1/2} = d_k 1_{n^{1/2}\hat{\omega}_k^{1/2} < \frac{\sqrt{2\log\log n}}{\sqrt{n}}} , \quad k=1,\ldots,m \tag{7}$$

Where $1_{n^{1/2}\hat{\omega}_k^{1/2} < \frac{\sqrt{2\log\log n}}{\sqrt{n}}}$ is the indicator function.
The test distribution is estimated by the stationary bootstrap of Politis and Romano (1994). The first step is to create time-series samples of the differences, and then calculate their sample average,

\[ \bar{d}_{b} = n^{-1} \sum_{t=1}^{n} d_{b,t}, \quad b=1,...,B \]  

(8)

The test statistic requires estimates of its variance, \( \sigma_{k}^{2} \), for \( k=1,...,m \). To obtain it under the null hypothesis, the bootstrap variable must be recentered, about \( \mu_{l}^{*} \), \( \mu_{c}^{*} \) or \( \mu_{u}^{*} \) by

\[ Z_{k,b,t} = d_{k,b,t} - g_{i}(d_{k}) \quad i = l,c,u, \quad b = 1,...,B, \quad t = 1,...,n \]  

(9)

Where \( g_{l}(x) = \max(0,x) \), \( g_{c}(x) = x \times 1_{x < -\sqrt{2 \log \log n}} \), and \( g_{u}(x) = x \).

Finally the test statistic is given by

\[ T_{b,n}^{SPA} = \max \left\{ 0, \max_{k=1,...,n} \left[ \frac{\sqrt{n}}{\sigma_{k}} \bar{Z}_{b,k} \right] \right\} \]  

(10)

And the p-value is

1. \( \bar{p}_{SPA} = \sum_{b=1}^{B} \frac{1}{B} \left| \bar{Z}_{b,n}^{SPA} \right| \)  

(11)

Where the null hypothesis is rejected for small values. Thus obtaining three values, one for each one of the estimators \( \mu_{l}^{*} \), \( \mu_{c}^{*} \) and \( \mu_{u}^{*} \).

For a more detailed description of the procedure of this test please refer to Hansen (2005) and the references therein.
5. RESULTS AND ANALYSIS

The results of the trading rules can be analyzed in a multitude of ways. In particular, they can be evaluated with and without benchmarks, with and without measures to forecast accuracy, by group of rules, or by period.

Faced with those possibilities, the approaches that I choose are the ones that, in a reasonable extent, in my opinion allow for an in depth analysis of the results.

Consequently, follows a brief presentation of the average annualized returns, the excess returns obtained over both benchmarks, each made by year and for the entire period, and for each category of trading rules.

Additionally, I extend the analysis by comparing the duration and the number of trades of the best rule, the winning (trading rules that yield positive returns) and the losing rules (trading rules that yield negative returns) in each of the trading categories.

Finally, the results obtained for the SPA test are presented.

5.1. Results for the average return criterion

5.1.1. Overview

The analysis of the results obtained for the entire period from January 2000 to December 2010, resumed on Table 3, allow to conclude that the filter rules family is the one with higher average return, followed by support and resistance, channel breakouts and, finally, by the moving averages family, which is the only group presenting a negative average return.

Regarding the average return of the best rule in each family, the filter rules is also the family with the best performing rule. The other families’ best rule have quite similar values, being the support and resistance the one with the worst performance.
In terms of the average duration of trade it is noticeable on Table 3 that the best performing rule in each family has much lower duration than the entire family average, being the only exception the filter rules, for which the duration of the best rule, although being smaller, it is much more closer to the average duration of the whole family.

Contrarily, the number of trades presents the opposite trend. The average for the family is lower than the number of trades used by the best rule. Once again, the discrepancy in values is great with the exception of the filter rules.

Still regarding the number of trades, the losing rules use, on average, more trades than the winning rules for 3 out of the 4 families. Only the channel breakouts winning rules are able to use more transactions than the losing ones.

Additionally, Figure 3 reports the average returns in each year under analysis and then for the entire period. The returns are annualized with no consideration of costs, no benchmarks and without filtering for data mining.

At a first glance it is apparent the high average return of most rules of the filter rules family, at least for the first three years, then the returns fade away and tend to be closer to zero, as most rules from the other trading families.

On those first three years it is also noticeable that the group of rules belonging to the channel breakouts are the ones, by what seems to be a large margin, with worst performance overall. During that period, although there are a lot of rules on the moving average family which present negative returns, there are quite a few rules with higher returns than the best of the channel breakouts family.

In the fourth year, as previously referred, there seems to be a reduction on the average return of most rules under the group of filter rules. The same can be said to occur to the moving averages and to the support and resistance rules. The opposite can be said for some rules of the channel breakouts, as they seem to improve.

In the next four years the general conclusion that arises is the same. The filter rules, the moving averages and the support and resistance rules seem to decrease in returns, and most of rules of the channel breakouts tend to grow.

In 2008 there is again some noticeable variation. Filter rules increase again in average return, assuming again the only positive values and the highest returns.

Afterwards, in the next two years the average return absolute values tend to decrease, being closer to zero in all families of trading rules.
Finally, regarding the averages over the entire period of all trading rules tested, it is possible to attest that the ones with higher average return belong to the filter rules. This family is, also, the one that visibly has a better performance globally, since none of their rules are negative, and the worst one has a higher absolute value than some rules in the other three trading family rules.

This can be better evaluated on Figure 4, where it is also possible to see that a good part of all rules on the moving averages family result on negative average return, whereas the other families seem to have only positive or null values.

Table 3 – Average properties by trading family, for the entire period.¹

<table>
<thead>
<tr>
<th>Rule Family</th>
<th>FR</th>
<th>MA</th>
<th>SR</th>
<th>CB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Return</td>
<td>3.8E-05</td>
<td>-1.0E-07</td>
<td>1.2E-05</td>
<td>7.0E-07</td>
</tr>
<tr>
<td>Mean Return (Best)</td>
<td>7.5E-05</td>
<td>5.1E-05</td>
<td>4.6E-05</td>
<td>5.0E-05</td>
</tr>
<tr>
<td>Mean Duration of Trade</td>
<td>128.3</td>
<td>67,507.0</td>
<td>31,636.0</td>
<td>388,136.4</td>
</tr>
<tr>
<td>Mean Duration of Trade (Best)</td>
<td>121.2</td>
<td>131.9</td>
<td>39.4</td>
<td>229.1</td>
</tr>
<tr>
<td>Mean Number of Trades</td>
<td>184,345.8</td>
<td>18,091.9</td>
<td>67,215.4</td>
<td>877.3</td>
</tr>
<tr>
<td>Mean Number of Trades (Best)</td>
<td>185,952.0</td>
<td>89,782.0</td>
<td>227,465.0</td>
<td>50,986.0</td>
</tr>
<tr>
<td>Mean Number of Winning Trades</td>
<td>48,897.5</td>
<td>5,953.4</td>
<td>13,308.2</td>
<td>404.7</td>
</tr>
<tr>
<td>Mean Number of Winning Trades (Best)</td>
<td>69,989.0</td>
<td>26,103.0</td>
<td>44,251.0</td>
<td>26,248.0</td>
</tr>
<tr>
<td>Mean Number of Losing Trades</td>
<td>77,951.7</td>
<td>6,051.0</td>
<td>20,442.5</td>
<td>35.5</td>
</tr>
<tr>
<td>Mean Number of Losing Trades (Best)</td>
<td>115,960.0</td>
<td>45,220.0</td>
<td>72,288.0</td>
<td>57.0</td>
</tr>
</tbody>
</table>

¹ FR, MA, SR and CB are, respectively, the abbreviations for filter rules, moving averages, support and resistance and channel breakouts.
The analysis to the returns using the own index as benchmark is identical to the preceding. By analyzing Figure 5 and Figure 6 it is not possible to discern both evaluations.

Figure 3 – Average annualized return, by year (annualized values).

Figure 4 – Average return per rule, over the entire period (2000 to 2010), annualized values.
In fact, the conclusions that jump out are that for the first three years there are a lot of rules on the filter rules family that present high excess returns on average. This tends to fade away in the next three years, when a group of rules on the channel breakouts take the lead on the excess returns. From that period on that lead also disappears and most families of rules remain unchanged.

Figure 5 – Average excess return over the buy and hold strategy, by year (annualized values).
The previous analysis sheds some light on the average excess return of the trading rules over the risk free rate.

Indeed, it comes as no surprise that the filter rules are the ones with higher excess return for the first four years, and that after that there is a tendency for all rules to decrease the absolute value of the excess return, with an exception in 2008 (please refer to Figure 7).

The major difference when comparing the average excess returns over the risk free rate, on Figure 7, to the returns over the buy and hold strategy, on Figure 6, is the magnitude of the negative excess return for almost half rules of the moving averages family.

Additionally, it is possible to infer from Figure 8 that the results obtained over the entire period under consideration are very similar to the ones obtained using the index benchmark.
Figure 7 - Average excess return over the risk free rate, by year.

Figure 8 - Average excess return over the risk free rate, for the entire period.
5.1.2. Duration of trades

On Figure 9, Figure 10, Figure 11 and Figure 12 are presented the average duration of trade for each group of trading rules, the filter rules, the moving averages, the support and resistance and the channel breakouts, respectively. In each graph it is presented the annual average for all rules that belong to that group and then the annual average for the trading rule with better performance, also, from that group.

The most relevant conclusion is that the best rule in each group has duration much lower than the average for the group, overall.

Specifically, for the filter rules represented on Figure 9, the yearly average is on the interval from 9 to 15 periods of 5 minutes, or 45 to 75 minutes. Whereas the best rule duration is around the average of 2 periods, or 10 minutes, for 7 years, and for the other 4 years goes as high as 31 and 50 periods (155 and 250 minutes, respectively).

The moving averages (Figure 10) have higher durations than the filter rules, on average. The annual average is situated on the interval from 3000 to 3100 periods of 5 minutes, or 15000 minutes to 15500 minutes. While the best rule average spends around 5 to 9 periods of 5 minutes (25 to 45 minutes), in total, on the market, with the exception of the year of 2007, on which the best rule average duration is more than 60 periods (300 minutes).

Consulting Figure 11 it is possible to infer that the support and resistance best rule duration ranges, on average, from 2 to 6 periods of 5 minutes (10 to 30 minutes) and the whole rules average around 1400 periods (7000 minutes).

Moreover, the channel breakouts, with graph on Figure 12, have on average the highest time of trading. The group average is always more than 16000 periods of 5 minutes (80,000 minutes), and the best rule is on the interval from 5 to 75 (25 to 375 minutes), each year.

Finally, Table 4 shows the difference between the average duration of trade for the entire family and the best rule. It stands out that even for the family presenting less discrepancy between its average and the best rule, it has almost 4 times the duration of the best rule. The other families’ discrepancy is, literally, multipliable by thousands.
Figure 9 – Mean duration of trade by year, for the Filter Rules group.

Figure 10 - Mean duration of trade by year, for the Moving Averages group.
Figure 11 – Mean duration of trade by year, for the Support and Resistance group.

Figure 12 - Mean duration of trade by year, for the Channel Breakouts group.
Table 4 - Comparison of the average trading duration for the entire period, by group of rules.

<table>
<thead>
<tr>
<th>Family of Trading Rules</th>
<th>All Rules</th>
<th>Best Rule</th>
<th>All/Best</th>
</tr>
</thead>
<tbody>
<tr>
<td>Filter Rules</td>
<td>50.5</td>
<td>13.1</td>
<td>3.9</td>
</tr>
<tr>
<td>Moving Averages</td>
<td>167,475.0</td>
<td>29.5</td>
<td>5,686.8</td>
</tr>
<tr>
<td>Support and Resistance</td>
<td>78,480.0</td>
<td>10.9</td>
<td>7,233.2</td>
</tr>
<tr>
<td>Channel Breakouts</td>
<td>755,000.0</td>
<td>55.3</td>
<td>13,652.8</td>
</tr>
</tbody>
</table>

5.1.3. Number of trades

The analysis on the number of trades for each group of rules allows to conclude that, for most years, the average annual number of trades in each trading group is lower than the annual average for the rule with the best performance in each of those families.

On Figure 13, Figure 14, Figure 15 and Figure 16, we observe that the mean number of trades in each year is relatively constant, for the group average. In the opposite spectrum, the best rule for each group, doesn’t seem to be within a constant range of values through the years.

Indeed, regarding the filter rules family, on Figure 13 we find that the best rule uses, in each year’s average, from 500 to 12000 transactions. Whereas the group average ranges from 7000 to 10000 transactions.

The moving averages number of transactions, presented on Figure 14, is much more constant than the filter rules. The average for the best rule, with the exception of the year of 2007 when the number of transactions is just above 400, is higher than 3000 and lower than 5000, and the entire group has around 800 trades in each year for the period analyzed.

For the support and resistance group of rules (Figure 15), the average number of trades is higher than for the moving averages, but still less than the filter rules. In fact, the group average assumes values around 3000 transactions each year, while the best rule surpasses several years the 4000 trades up to the 12000 mark.

Finally, on Figure 16, we attest that the mean number of transactions for both the whole channel breakouts group and the best rule on the group is also quite variable. In the first three years the mean number is around 20 transactions, increasing in the next three years to the maximum value of 108 trades. From this point on, the value decreases again reaching a minimum of 7 transactions in 2008. The best rule presents exactly the same trend, with the only difference being the values, which range from 350 to 6000 trades.
Figure 13 - Mean number of trades by year, for the Filter Rules group.

Figure 14 - Mean number of trades by year, for the Moving Averages group.
Figure 15 - Mean number of trades by year, for the Support and Resistance group.

Figure 16 - Mean number of trades by year, for the Channel Breakouts group.
5.1.4. Number of winning and losing trades

In this section I analyze the number of trades where the trading rules generate positive returns, from now on referred as winning trades, and when trades generate negative returns, entitled, from now on, as losing trades.

In fact, Figure 17 shows that, in most years, the average winning filter rules use fewer transactions than the rule, from that subgroup, which generates higher returns. The same is also true for the losing trades, the average number of trades for the entire losing rules, for most years, are less than the ones used by the best rule of the losing rules.

These conclusions are in line with the ones obtained from the previous analysis on the number of trades. The best trading rules tend to use more transactions.

Having said that, the one different conclusion that can be drawn from the current analysis is that the winning trades undergo, on average, on fewer trades than the loosing ones. The same is relatable to the best trade in each situation (losing and winning), the best rule of the winning trades uses, on average, less trades than the best rule of the losing trades, in each year.

Regarding the other families of trading rules the results are similar (Figure 18, Figure 19 and Figure 20), with the channel breakouts, presented on Figure 20, the only exception.

Indeed, the channel breakouts winning trades, both for the entire group and the best rule, have more transactions than the average for the losing trades.
Figure 17 - Mean number of winning/losing trades by year, for the Filter Rules group.

Figure 18 - Mean number of winning/losing trades by year, for the Moving Averages group.
Figure 19 - Mean number of winning/losing trades by year, for the Support and Resistance group.

Figure 20 - Mean number of winning/losing trades by year, for the Channel Breakouts group.
5.1.5. Returns

The analysis of the mean returns per group of rules allows to easily deduce that most rules start by having positive and (mostly) constant average returns, in the first three years, but decrease afterwards, and, in some cases, they experience a new growth in 2008.

In specific, this trend is seen on the filter rules (Figure 21), on the moving averages (Figure 22) and on the support and resistance (Figure 23). The only exceptions to what has been said is the average for the entire set of rules for the moving averages and the channel breakouts, which register an annual value close to or equal to zero for most years, and the best rules average for the channel breakouts which records the opposite behavior compared to the other groups.

Figure 21 – Mean return by year, for the Filter Rules group.
Figure 22 - Mean return by year, for the Moving Averages group.

Figure 23 - Mean return by year, for the Support and Resistance group.
5.2. Superior Predictive Ability test

The results obtained from the SPA test, presented on Table 5, allow to conclude that the null hypothesis is not rejected for any level (10, 5 or 1%) and over any of the sub-periods (years) analyzed.

Indeed, the consistent value assumes its lowest value in the year of 2005, even though, being higher than 60%. In all other years, and in the entire period, the consistent value is around 80%.

Therefore no rule appears to be able to provide an average return statistically higher than the one given by a buy and hold strategy.
Table 5 - SPA test results.

<table>
<thead>
<tr>
<th>Year</th>
<th>Consistent</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>0.848</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>2001</td>
<td>0.854</td>
<td>0.016</td>
<td>1.000</td>
</tr>
<tr>
<td>2002</td>
<td>0.775</td>
<td>0.008</td>
<td>1.000</td>
</tr>
<tr>
<td>2003</td>
<td>0.855</td>
<td>0.002</td>
<td>1.000</td>
</tr>
<tr>
<td>2004</td>
<td>0.833</td>
<td>0.021</td>
<td>0.987</td>
</tr>
<tr>
<td>2005</td>
<td>0.611</td>
<td>0.016</td>
<td>0.650</td>
</tr>
<tr>
<td>2006</td>
<td>0.773</td>
<td>0.014</td>
<td>0.926</td>
</tr>
<tr>
<td>2007</td>
<td>0.882</td>
<td>0.087</td>
<td>0.986</td>
</tr>
<tr>
<td>2008</td>
<td>0.871</td>
<td>0.228</td>
<td>1.000</td>
</tr>
<tr>
<td>2009</td>
<td>0.752</td>
<td>0.028</td>
<td>0.810</td>
</tr>
<tr>
<td>2010</td>
<td>0.844</td>
<td>0.078</td>
<td>0.929</td>
</tr>
<tr>
<td>All</td>
<td>0.974</td>
<td>0.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>
6. CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORK

Given the state of the art on this topic, and despite the ongoing debate, from the start my expectation was that technical trading rules would not be profitable even under a high-frequency time frame.

Nonetheless, more than 60 years after the first endeavors in this area there is still a lot of discussion on the topic.

In addition, the literature on intraday technical trading alludes to a few simple conclusions. Such studies are relatively recent, most of them, probably due to technical difficulties, use datasets no longer than one year, and most of them do not employ robustness tests.

This study adds to the current literature by analyzing a substantially larger period of intraday data than previous studies, and by comparing the trading rules using the Superior Predictive Ability test (Hansen, 2005) to account for data snooping.

6.1. Conclusions

The results obtained do not leave much margin to interpretation. The fact is that the 5680 technical trading rules tested do not generate abnormal returns. This attests for the efficiency of prices of the FTSE 100 index on the 11 years from January 2000 to December 2010.

Effectively, this is a conclusion obtained even without the consideration of transaction costs. The results obtained prior to the consideration of the SPA test by Hansen (2005), already seem to indicate that the rules tested do not outperform the market. The robustness test confirmed that, and the consideration of taxes and fees would only reinforce the results.

Indeed, comparing to existing studies on this subject, at least the ones that account for data snooping and conduct, up to date, robustness tests, the conclusion is similar. The random walk hypothesis and the EMH hold.
Marshall et al. (2008), Duvignage et al. (2013) and Chaboud et al. (2014) are examples of studies that conduct similar tests over different markets/indexes with the consideration of data snooping measures, leading to the same conclusions.

Studies like Wood et al. (1985), Los (1999), Busse and Green (2002), Cassese and Guidolin (2004), Chordia et al. (2005) and Manahov et al. (2014), besides being conducted on intraday datasets, they all have in common the fact that they state that markets are in some way inefficient and the non inclusion of robustness tests to their results, or the inclusion of outdated tests that are not the best to account for the results, overall, significance.

In fact, here lies one of the most important achievements of this study, not only it provides evidence that FTSE 100 index price incorporates historical information, but also uses a robust test methodology. Being that the most likely cause for obtaining different results from similar studies.

In addition, the analysis made on the duration and number of trades prompts a great insight on the value of most, if not all, technical trading rules tested. The fact is that for all groups of rules tested the best performing rule has much less time of exposure than the average for all rules. This means that the less time a portfolio is on the market for a given rule, the better is its performance.

In fact, this can be indicative that the technical trading rules tested don’t generate value on their own merits, but their results may simply be due to luck and to a small exposure to the market. If that was not the case and if indeed the rules tended to increase value when used, the more time of usage the higher would be their returns, or at least its performance would not exhibit such a notorious inversely correlated pattern.

### 6.2. Suggestions for future research

Even though the work accomplished was beyond the initial expectations, the technical challenges that derived from working with such a large dataset of returns and rules prevented me to explore the results even further.

Although the current work makes a small contribution to the state of the art on the field of finance, in the sense it confirms the validity of the weak form of the EMH and the random walk hypothesis on an intraday dataset and using the SPA test, there is still a lot of room to improve this study in the future.
Firstly, the current study uses an index, and this is not a traded financial instrument, and consequently these results would not be easily replicated in practice by an investor. So, the usage of data from a tradable asset would be a substantial advantage.

Secondly, a different set of technical trading rules could be used. Although the rules used in this study are fairly comprehensive, encompassing the most number of rules used in past research, some recent studies point out other types of rules that can be used. For example, a dynamic process to find trading rules can be used, in which an iterative process finds in each step the best combination of single parameters to be used on a given rule for it to achieve better performance.
REFERENCES


Mandelbrot, B. (1962). The variation of certain speculative prices. Research Note NC-87, IBM.


## APPENDIX

### Appendix 1 – Observations out of chronological order (eliminated from the dataset).

<table>
<thead>
<tr>
<th>Date</th>
<th>Time</th>
<th>Price</th>
<th>Date</th>
<th>Time</th>
<th>Price</th>
<th>Date</th>
<th>Time</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>30/11/2009</td>
<td>08:00:54</td>
<td>5256.98</td>
<td>30/11/2009</td>
<td>10:00:45</td>
<td>5206.28</td>
<td>30/11/2009</td>
<td>11:36:27</td>
<td>5207.99</td>
</tr>
<tr>
<td>30/11/2009</td>
<td>08:00:57</td>
<td>5261.92</td>
<td>30/11/2009</td>
<td>10:02:52</td>
<td>5208.25</td>
<td>30/11/2009</td>
<td>11:37:01</td>
<td>5210.29</td>
</tr>
<tr>
<td>30/11/2009</td>
<td>08:04:01</td>
<td>5257.12</td>
<td>30/11/2009</td>
<td>10:12:22</td>
<td>5206.47</td>
<td>30/11/2009</td>
<td>12:00:02</td>
<td>5208.32</td>
</tr>
<tr>
<td>30/11/2009</td>
<td>08:04:30</td>
<td>5258.51</td>
<td>30/11/2009</td>
<td>10:13:09</td>
<td>5207.06</td>
<td>30/11/2009</td>
<td>12:00:05</td>
<td>5208.54</td>
</tr>
</tbody>
</table>
Appendix 2 – Trading Rules Parameters

The parameters considered were the ones on Sullivan et al. (1999), with some adjustments to account for the fact that the database under evaluation is composed of intraday data, so all non-integer parameters were divided by the number of days on a year to the power of 1/288, being 288 the number of 5 minutes periods in a trading day.

\[
\left(1 + \frac{\text{DailyParam}}{\text{IntradayParam}} \right)^{\frac{1}{288}} - 1 = \text{IntradayParam}
\]

2.1. Filter rules

\(x\) = change in price \((x \times \text{price})\) required to initiate a position;
\(y\) = change in price \((y \times \text{price})\) required to liquidate a position (must be less than \(x\));
\(e\) = used for an alternative definition of extrema where a low (high) can be defined as the most recent price that is less (greater) than the \(n\) previous prices;
\(c\) = number of periods a position is held, ignoring all other signals during that time;
\[x = 0.0000173180024236608, 0.0000345503567567018, 0.0000516979074496327, 0.000068761486518909, 0.0000857419137887394, 0.000102639997129561, 0.000119456532687412, 0.000136192305112193, 0.000152848087775936, 0.000169424642988858, 0.000202343066249888, 0.000234953459997911, 0.00026726154283004, 0.000299272885145196, 0.000330922890382964, 0.000393579811755806, 0.000455056275412066, 0.000515480054197104, 0.000574868084739055, 0.000633261386471906, 0.000775104235773094, 0.000911402104117887, 0.00116898911290808, 0.0014085646582889 [24 values];
\[y = 0.0000173180024236608, 0.0000345503567567018, 0.0000516979074496327, 0.000068761486518909, 0.0000857419137887394, 0.000102639997129561, 0.000119456532687412, 0.000136192305112193, 0.000152848087775936, 0.000169424642988858, 0.000202343066249888, 0.000234953459997911, 0.00026726154283004, 0.000299272885145196, 0.000330922890382964, 0.000393579811755806, 0.000455056275412066, 0.000515480054197104, 0.000574868084739055, 0.000633261386471906, 0.000775104235773094, 0.000911402104117887, 0.00116898911290808, 0.0014085646582889 [24 values];
\(e = 1, 2, 3, 4, 5, 10, 15, 20 [8 values];
\(c = 5, 10, 25, 50 [4 values].

2.2. Moving averages

\(n\) = number of periods in a long period moving average;
\( m = \) number of periods in a short period moving average;
\( b = \) fixed band multiplicative value;
\( d = \) number of periods for the time delay filter;
\( c = \) number of periods a position is held, ignoring all other signals during that time;
\( n = 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 200, 250 \) [14 values];
\( m = 2, 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 200 \) [14 values];
\( b = 0.0000034704932898, 0.0000173180024236608, 0.0000345503567567018, 0.0000516979074496327, 0.000068761486518909, 0.000102639997129561, 0.000136192305112193, 0.000169424642988858 \) [8 values];
\( d = 2, 3, 4, 5 \) [4 values];
\( c = 5, 10, 25, 50 \) [4 values].

### 2.3. Support and resistance

\( n = \) number of periods in the support and resistance range;
\( b = \) fixed band multiplicative value;
\( d = \) number of periods for the time delay filter;
\( c = \) number of periods a position is held, ignoring all other signals during that time;
\( n = 5, 10, 15, 20, 25, 50, 100, 150, 200, 250 \) [10 values];
\( b = 0.0000034704932898, 0.0000173180024236608, 0.0000345503567567018, 0.0000516979074496327, 0.000068761486518909, 0.000102639997129561, 0.000136192305112193, 0.000169424642988858 \) [8 values];
\( d = 2, 3, 4, 5 \) [4 values];
\( c = 5, 10, 25, 50 \) [4 values].

### 2.4. Channel Breakouts

\( n = \) number of periods for the channel;
\( x = \) difference between the high price and the low price \((x \times \text{price})\) required to form the channel;
\( d = \) number of periods for the time delay filter;
\( c = \) number of periods a position is held, ignoring all other signals during that time;
\( n = 5, 10, 15, 20, 25, 50, 100, 150, 200, 250 \) [10 values];
\[ x = 0.0000173180024236608, 0.0000345503567567018, 0.000068761486518909, \\
0.00010263997129561, 0.000169424642988858, 0.000251144939873882, \\
0.000330992890382964, 0.000485402291719561 \text{ [8 values];} \]
\[ d = 2, 3, 4, 5 \text{ [4 values];} \]
\[ c = 5, 10, 25, 50 \text{ [4 values].} \]