ISCTE Business School
Instituto Universitário de Lisboa

TECHNICAL ANALYSIS

A NEW LOOK AT AN OLD INDICATOR: THE PARABOLIC STOP-AND-REVERSAL

Tiago Miguel Costa Rodrigues

Project submitted as a partial requirement for the conferral of the Master of Science in Finance degree

Supervisor:
Prof. Doutor José Dias Curto, Associate Professor ISCTE – IUL Business School, Quantitative Methods for Management and Economics Department

September 2015

- Spine -

A NEW LOOK AT AN OLD INDICATOR: THE PSAR

Tiago Miguel Costa Rodrigues

ISCTE Business School
Instituto Universitário de Lisboa

Resumo

Gerir riscos de transação e preservação de capital é um dos tópicos mais relevantes para investidores de sucesso. Esta dissertação examina a utilidade do indicador Parabolic Stop-and-Reversal (PSAR) como estratégia de investimento, bem como estratégia de limitação de perdas, contra o conhecimento comum de que os ativos financeiros devem ser comprados e mantidos em carteira. Foi utilizada uma série de dados constituída por 10 ativos diferentes, respeitante ao período compreendido entre 01/01/2000 e 01/01/2015. Os ativos selecionados foram as taxas de câmbio EUR/USD e USD/JPY; os Exchange-Traded Funds iShares MSCI Japan, SPDR SP500 e iShares EURO STOXX 50 UCITS; a acção da Toyota, Portugal Telecom e JP Morgan Chase; e por último as matérias primas Ouro e Brent. Para além dos habituais testes estatísticos, foi aplicada um metodologia de *bootstraping* no sentido de melhorar a validação dos resultados obtidos. Os resultados demonstram a ineficácia do PSAR, resultante do facto de este não conseguir distinguir corretamente os momentos em que os investidores devem inverter ou fechar as suas posições.

Classificação JEL: G11, G14, G17

Palavras-Chave: Parabolic Stop-and-Reversal, Average Directional Index, Hipótese dos Mercados Eficientes, Análise Técnica

Abstract

Managing trading risk and capital preservation is one of the main issues for successful traders. This study examines the usefulness of the Parabolic Stop-and-Reversal (PSAR) indicator both as a trading strategy, as well as a stop-loss strategy, when compared to the common knowledge that assets should be bought and held. We use a data set of 10 assets, covering the period from 01/01/2000 to 01/01/2015. The selected assets are the EUR/USD and USD/JPY exchange-rates; the iShares MSCI Japan, the SPDR SP500 and the iShares EURO STOXX 50 UCITS Exchange-Traded Funds; the common stock of Toyota, Portugal Telecom and JP Morgan Chase; and lastly Gold and Brent. In addition to the standard statistical tests, we apply a bootstrapping methodology to further validate results. The results highlight the lack of trading abilities by the PSAR, as it cannot properly determine where positions should be reversed or exited.

JEL Classification: G11, G14, G17

Keywords: Parabolic Stop-and-Reversal, Average Directional Index, Efficient Markets Hypothesis, Technical Analysis

Acknowledgments

A special acknowledgement is due to Professor José Dias Curto for his readiness to help and is valuable insights. In addition I would like to thank my parents and girlfriend for caring and keeping me in the right track to achieve my goals. This work is also yours.

Figures Index

Figure 1 - Application of the PSAR system 4
Figure 2 - PSAR system and whipsaws 5
Figure 3 - ADX application 6
Figure 4 - PSAR adjustment for t+1 if investors are long 15
Figure 5 - PSAR adjustment for t+1 if investors are short 15
Figure 6 - +DM 16
Figure 7 - -DM 17
Figure 8 - Possible combinations for a given day TR 17
Figure 9 - Trading scheme for Strategy 1 22
Figure 10 - Trading scheme for Strategy 2 23
Figure 11 - Trading scheme for Strategy 3 24
Figure 12 - Uptrend PSAR calculation and illustration 63
Figure 13 - Downtrend PSAR calculation and illustration 63
Figure 14 - Evolution of Brent asset prices 64
Figure 15 - Evolution of EUR/USD asset prices 66
Figure 16 - Evolution of JP Morgan Chase asset prices 68
Figure 17 - Evolution of MSCI Japan ETF asset prices 70
Figure 18 - Evolution of Portugal Telecom asset prices 72
Figure 19 - Evolution of S&P500 SPDR ETF asset prices 74
Figure 20 - Evolution of Eurostoxx 50 asset prices 76
Figure 21 - Evolution of Toyota asset prices 78
Figure 22 - Evolution of USD/JPY asset prices 80
Figure 23 - Evolution of Gold asset prices 82

Tables Index

Table 1 - Number of observations for each asset 39
Table 2 - Characterization of Strategies 1 and 2 (Average Results) 40
Table 3 - Characterization of Strategies 1 and 2 (Average Results) (Continuation)...... 40
Table 4 - Strategies 1 and 2 Returns Vs. BH (Average Daily Returns) 41
Table 5 - Strategies 1 and 2 Risk Vs. BH (Average Daily Variance) 43
Table 6 - Strategies 1 and 2 R3 Vs. BH 44
Table 7 - *T-Test* for Strategy 1........ 45
Table 8 - *T-Test* for Strategy 2........ 45
Table 9 - Results from applying the WRC to Strategy 1........ 46
Table 10 - Results from applying the WRC to Strategy 2........ 47
Table 11 - Characterization of Strategy 3 (Average Results)........ 48
Table 12 - Characterization of Strategy 3 (Average Results) (Continuation)........ 48
Table 13 - Strategy 3 Returns Vs. BH (Average Daily Returns) 49
Table 14 - Strategy 3 Risk Vs. BH (Average Daily Variance)........ 50
Table 15 - Strategy 3 R3 Vs. BH........ 51
Table 16 - *T-Test* for Strategy 3........ 51
Table 17 - Results from applying the WRC to Strategy 3........ 52
Table 18 - Strategies Characterization........ 64
Table 19 - Strategies Characterization (Continuation) 65
Table 20 - Risk and Returns analysis for Brent........ 65
Table 21 - *T-Test* for Brent........ 65
Table 22 - Strategies Characterization........ 66
Table 23 - Strategies Characterization (Continuation) 67
Table 24 - Risk and Returns analysis for EUR/USD 67
Table 25 - *T-Test* for EUR/USD........ 67
Table 26 - Strategies Characterization........ 68
Table 27 - Strategies Characterization (Continuation) 69
Table 28 - Risk and Returns analysis for JP Morgan Chase 69
Table 29 - *T-Test* for JP Morgan Chase........ 69
Table 30 - Strategies Characterization........ 70
Table 31 - Strategies Characterization (Continuation) 71
Table 32 - Risk and Returns analysis for MSCI Japan ETF........ 71

Table 33 - *T-Test* for MSCI Japan ETF 71
Table 34 - Strategies Characterization 72
Table 35 - Strategies Characterization (Continuation) 73
Table 36 - Risk and Returns analysis for Portugal Telecom 73
Table 37 - *T-Test* for Portugal Telecom 73
Table 38 - Strategies Characterization 74
Table 39 - Strategies Characterization (Continuation) 75
Table 40 - Risk and Returns analysis for S&P 500 SPDR ETF 75
Table 41 - *T-Test* for S&P 500 SPDR ETF 75
Table 42 - Strategies Characterization 76
Table 43 - Strategies Characterization (Continuation) 77
Table 44 - Risk and Returns analysis for Eurostoxx 50 77
Table 45 - *T-Test* for Eurostoxx 50 77
Table 46 - Strategies Characterization 78
Table 47 - Strategies Characterization (Continuation) 79
Table 48 - Returns and Risk analysis for Toyota 79
Table 49 - *T-Test* for Toyota 79
Table 50 - Strategies Characterization 80
Table 51 - Strategies Characterization (Continuation) 81
Table 52 - Risk and Returns analysis for USD/JPY 81
Table 53 - *T-Test* for USD/JPY 81
Table 54 - Strategies Characterization 82
Table 55 - Strategies Characterization (Continuation) 83
Table 56 - Risk and Returns analysis for Gold 83
Table 57 - *T-Test* for Gold 83

Acronyms

TA – Technical Analysis

PSAR – Parabolic Stop-and-Reversal

BH – Buy-and-Hold strategy

ADX – Average Directional Index

ETF's – Exchange-Traded Funds

EMH – Efficient Markets Hypothesis

RWH – Random Walk Hypothesis

BF – Behavioural Finance

WRC – White Reality Check

DM – Directional Movement

TR – True Range

DI – Directional Indicator

DX – Directional Movement Index

R3 – Return to Risk Ratio

Contents

Resumo I

Abstract.. II

Acknowledgments III

Figures Index IV

Tables Index V

Acronyms VII

Contents VIII

Executive Summary XI

1. Introduction 1

2. Literature Review 3

2.1. Academic Research on Technical Analysis 3

2.2. Parabolic Stop-and-Reversal 4

2.3. Stop-loss Strategies 6

2.4. Efficient Market Hypothesis, Random Walk Theory and Dow’s Theory 7

2.5. Behavioral Finance 8

2.6. White’s Reality Check 10

3. Methodology 12

3.1. Hypothesis 12

3.2. Technical Analysis Indicators 13

3.2.1. Parabolic Stop-and-Reversal 13

3.2.2. Average Directional Index 16

3.3. Trading Strategies Implementation, Transaction Costs and Taxes 21

3.3.1. Trading Strategies Implementation 21

3.3.2. Transaction Costs and Taxes 24

3.4. Characterization, Returns and Risk Measurements 25

3.4.1. Characterization of each strategy 25

3.4.2. Returns 27

3.4.3. Risk and volatility measures 28

3.5. Statistical Validation of Results 29

3.5.1. *T-test* 29

3.5.2. White RC 32

3.5.3. Stationary Bootstrapping – The back bone of White's Reality Check 36

4. Data 39

5. Empirical Results 40

5.1. Strategy 1 & Strategy 2 40

5.1.1. Characterization 40

5.1.2. Returns 41

5.1.3. Risk 43

5.1.4. Statistical Validation of results– *T-test* 45

5.1.5. Statistical Validation of results – White RC 46

5.2. Strategy 3 48

5.2.1. Characterization 48

5.2.2. Returns 49

5.2.3. Risk 50

5.2.4. Statistical Validation of results – *T-test* 51

5.2.5. Statistical Validation of results – White RC 52

6. Discussion and conclusions 54

7. References 57

8. Appendix 61

Executive Summary

The main goal of every participant in financial markets is to maximize capital gains and enhance the value of investments. Nowadays, with the massification of trading mechanisms and platforms, every person, regardless of being a professional or simply an enthusiast, can easily invest in every type of assets imaginable.

The increase in the number of investors participating in financial market brought an old question back to the table: Fundamental Analysis or Technical Analysis (TA)? Which conceptual approach is better? Which should be used?

Despite not being a consensual choice among academics, more and more investors explore the branch of TA.

TA focuses not in the intrinsic value assets, but instead on the behavioural aspect of the markets, which is materialized in the form of technical indicators.

Nevertheless, although pure technical analysts believe that TA is the most correct way to trade the markets, they recognize that this method is not flawless. For that reason capital preservation tools are vital in maintaining a winning trading record.

With that end in mind, one particular technical indicator was developed: the Parabolic Stop-and-Reversal (PSAR). The goal of the PSAR is to predict the price levels at which a trending market will stop moving in one direction and reverse its current trend. By using this technical indicator, investors can decide whether to reverse or exit their positions, when these price levels are met.

In this dissertation we examine the usefulness of the PSAR both as a stop-loss strategy, as well as trading strategy, against the common knowledge that assets should be bought and held, i.e., the Buy-and-Hold strategy (BH). Moreover we seek to improve the results of the traditional PSAR by using it together with another trend measuring indicator: the Average Directional Index (ADX).

We test the PSAR in a data set of 10 assets, during a period of 15 years from 01/01/2000 to 01/01/2015. The selected assets are highly liquid and representative of several markets and industries.

Our results show that the PSAR is not able to determine correctly when investors should exit or reverse their positions and for that reason it misses its main goal. The results are further enforced by the application of the ADX, which worsens the performance of almost every asset in the data set. This indicates that the PSAR is making poor trading decisions, even when the market is moving in a clear trend.

The outcome of this dissertation supports the Efficient Markets Hypothesis (EMH) and the premise that one cannot expect to have superior future capital gains by making inferences based on past data.

1. Introduction

Ever since the inception of financial markets, investors have always sought out ways to maximize their profits. Consequently several methods of analysing price movements were developed, one of which is TA.

TA focuses on past actions and behaviours, with the aim of predicting future prices. Although the investing community accepts TA as a way of operating in the markets, academics raise issues about its usefulness, because it is inconsistent with fundamental theories, such as the EMH.

Despite the controversy, nowadays every online brokerage firm offers trading platforms composed mainly by TA tools. Still, there is a crucial aspect about technical trading which is often overlooked: trading risk management and capital preservation. According to Murphy (1999: 395) it is not possible to survive for long in the markets without a solid money management strategy. However as Tatro (2011: 128) claims "*The strategy of stops is a subject that is neither dissected nor discussed nearly enough*".

Notwithstanding the claims of Tatro (2011), there are several strategies that can be implemented, in order to help investors control the amount of risk they undertake.

One of these strategies is the PSAR. In fact the PSAR is one of the most versatile technical indicators to trade with because it can be used either as a dynamic trailing-stop or as a trading strategy by itself. The characteristics of this indicator allow it to always take current market momentum into account and place stop-loss orders or reverse orders accordingly. Due to the fact that the PSAR is more appropriate to trending markets, is it recommended to be used together with trend measuring indicators, namely the Average Directional Index (ADX).

Although there are a variety of studies that test the profitability of other technical indicators across several markets, there are few that test the capabilities of the PSAR.

Hence, the goal of our dissertation is to evaluate the effectiveness of the PSAR both as a trading strategy, as well as a stop-loss strategy. Additionally we compare it against the BH, and determine which performs better concerning risk and profitability. We test this indicator using a 15 years dataset of 10 different assets, composed by 2 exchange-rates, 3 Exchange-Traded Funds (ETF's) representative of world markets, 3 common stocks and 2 commodities.

The outcome of our dissertation is useful for investors, as it provides new insights about an often disregarded indicator. To the best of our knowledge, this is the first study that addresses the PSAR across such a diverse set of financial assets.

The remainder of this dissertation is structured as follows. In the following section we provide a review of what has been written about the PSAR and some other relevant topics such as TA or the EMH. Subsequently, in Section 3 we explain the methodologies we use to implement the different trading strategies and how we characterize them and to evaluate these same strategies. Thereafter, in Section 4 we refer the data set we use and explain the reasons that lead us to choose this group of assets. Next, in Section 5 we present the empirical results from our study. Lastly, in Section 6 we discuss and comment the results obtained and provide indications for future research.

2. Literature Review

In this section we briefly revise what has been written about particular topics related to the PSAR indicator, stop-loss strategies and the foundations of TA. These topics are the ones which better fit the prosecution of the proposed objectives.

2.1. Academic Research on Technical Analysis

TA builds upon the assumption that price changes are dependent, meaning that past price sequences are important to forecast upcoming prices. The premise is that history tends to repeat itself and therefore if one gets familiar with recursive price patterns, one may enhance future potential gains.

Although being fiercely criticized, TA is immensely utilized by practitioners[1] and studied by academics. Studies such as Brock *et al*. (1992) find evidence of profitability by using moving averages and trading range breakout rules on the Dow Jones Industrial Average. In addition Curcio and Goodhart (1992), along with Osler (2000), show that support and resistance levels, provided by technical analysts themselves, have forecasting powers in foreign exchange markets.

The evidence of profitability is further extended worldwide, with researches like the ones of Vidotto and Zambon (2009), who conclude that the Moving Average Convergence-Diverge indicator is an effective tool to determine entry points in the Brazilian stock market and Patão (2012) who shows that less well-known combinations of this same indicator prove to be profitable across a set of 30 diversified assets. In addition Chong *et al*. (2011), apply the On-Balance Volume indicator and prove that it can outperform the BH in geographically disperse ETF's.

Across European markets, there is also literature that highlights the results of TA. The work of Chong and Ng (2008) emphasizes the profitability of the Relative Strength Index on the London Stock Exchange and Metghalchi *et al*. (2012) test moving average strategies in 16 European countries, concluding that these rules have predictive power, particularly in markets with a small or medium capitalization. Another notable study is the one made by Lu and Chen (2013) who inspect the effectiveness of candlesticks patterns in Europe and find evidence of predictive power.

[1] For further reference on researches that illustrate the use of TA by practitioners see Menkhoff and Taylor (2007), Flanegin and Rudd (2005) and Taylor and Allen (1992).

Looking at TA from different perspective Dorfleitner *et al.* (2007: 9) test how it affects investment volatility and find that "*...it is at least dangerous, since it can damage the performance of the investment whereas the risk reduction effect is not granted.*".

2.2. Parabolic Stop-and-Reversal

The PSAR indicator is a trend-following system that focuses on helping investors capturing significant price moves, by indicating were they should place stop orders or revert their positions. Developed by Welles Wilder in 1978, it derives its name from the fact that the line generated by stop-loss levels resembles a parabola. One particular aspect about this indicator is that it behaves in function of both time and prices. Wilder (1978: 9) refers that "*This system allows room for the market to react for the first days after a trade is initiated and then the stops begin to move more rapidly*".

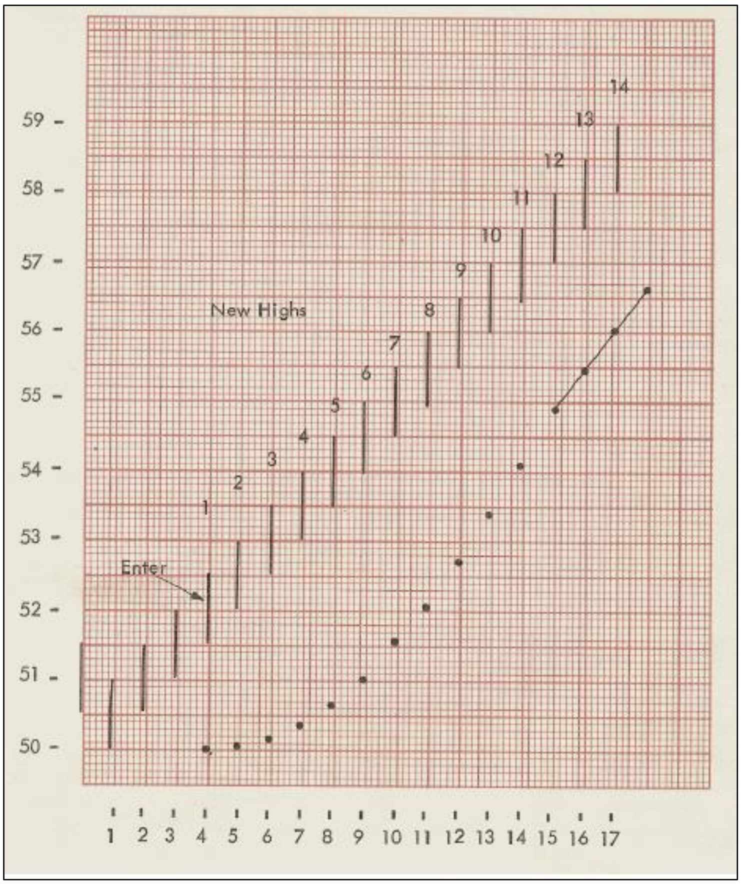

Figure 1 - Application of the PSAR system
Source: New Concepts in Technical Trading Systems - Page 10

The PSAR works in a conservative fashion, since the stop-loss levels that it proposes never move in the opposite direction in which the trade was first initiated (see Figure 1 and Figure 2) [2]. This means investors are never recommended to broaden stops beyond the point the PSAR is already specifying, even if prices evolve favourably. For example, if investors hold a long position and prices move upwards, their stop-loss is also going to move upwards, accompanying prices.

Figure 2 - PSAR system and whipsaws
Source: www.informedtrades.com, consulted on 18/11/2014

One potential pitfall about this indicator is the fact that it should only be used in trending markets, otherwise investors might get whipsawed as Figure 2 illustrates. In order to tackle this issue Wilder suggests using the PSAR together with the ADX.

The ADX is a technical indicator that helps investors determining if a market is experiencing a trending phase or if, on the other hand, it is facing a ranging phase, without a defined trend. According to Wilder (1978:47), a reading greater than 25 for the ADX is indicative that the market is trending. Conversely a reading below 25 indicates that the market is non-trending and therefore trend following indicators should be avoided (see Figure 3).

[2] In Figure 2, the stop-loss levels are the dotted lines above and below prices. Green dots signal stop-losses when the investor is long, and red dots signal stop-losses when the investor is short.

Figure 3 - ADX application
Source: www.fxmarketleaders.com, consulted on 14/06/2015

Despite the PSAR being a very versatile trading tool, academic literature about it is quite scarce.

Yazdi and Lashkari (2010) test the PSAR on four of the most traded exchange-rates worldwide, using hourly data from January 2001 to December 2010, and find signs of profitability for the EUR/USD and USD/JPY. Moreover they claim that the indicator produces more profitable buy signals than sell signals.

On a recent study, Metghalchi *et al*. (2014), apply a set of popular trading rules, among which the PSAR, to the Nairobi stock index, from 12/09/2006 to 18/04/2013. Although they find that some trading rules can beat the BH after transactions costs, the results for the PSAR are statistically irrelevant.

By taking an unconventional approach, Lim *et al.* (2014) show that the ADX can also be used separately from the PSAR. The authors explore the profitability of Bollinger Bands using the ADX to avoid trending markets, over 1995 until 2012, in six different indexes. Although they find little evidence of superior performance, they claim the ADX can still be effective in creating a systematic stop-loss strategy.

2.3. Stop-loss Strategies

According to Elder (2002: 171) "*Placing stops is one of the hardest challenges in trading, more so than finding good trades.*". However, as Kaminski and Lo (2014) refer "*Although stop-losses are widely used, the corresponding academic literature is rather limited* ".

Kaminski and Lo (2014) apply stop-losses to the regular BH, using U.S futures contracts as a trading instrument, from January 1993 to November 2011. They find that, at longer sampling frequencies, some stop-loss strategies add value over the BH portfolio returns, while at the same time reducing volatility. Moreover they claim that stop-loss policies help fighting some behavioural biases like the disposition effect.

Another study by Tooth (2014) analyses a stop-loss strategy proposed by O'Neil (1988). O'Neil claims that investors should limit losses to no more than 8% of the invested capital. Tooth examines this rule on a set of randomly selected portfolios, based on the Standard and Poor's 500, through 1969 to 2012, and finds evidence that this strategy "*does not accomplish what it proposes*". Tooth claims that, although this basic rule reduces the variance of returns, if investors rebalance their portfolio after being stopped out, variance is increased without any guarantee of increasing returns.

Following the approach of Vince (1990: 79), Libertini (2013) tests two contrarian strategies on the S&P500, between 31/12/1989 and 31/12/2012. Additionally the author explores two stop-loss strategies, one based on a fixed loss of 2%, and another on the Average True Range indicator. Libertini concludes that these stop-losses did not improve neither performance nor risk of short-term countertrends trades. Furthermore the author finds that these strategies do not perform well at increased volatility levels.

Despite the scarcity of academic studies about stop-loss strategies, various books on TA present diverse solutions investors can implement[3]. The strategies proposed in the referred literature have very dissimilar motivations, as they can rely upon the trader's psychological traits, as well as on more complex technical indicators like the PSAR.

2.4. Efficient Market Hypothesis, Random Walk Theory and Dow's Theory

There are two main theoretical arguments that challenge TA and the idea that prices are predictable. These are the Random Walk Hypothesis (RWH) and the EMH.

The RWH, made popular by Fama (1965a), Cootner (1962) and Cowles and Jones (1937), assumes that returns history has no memory. This means that prices evolve in a random motion and therefore any procedure that relies on past behaviours to predict future movements is fruitless. However several authors present arguments against the

[3] For further reference see: Tatro (2011: 125), Elder (2008: 165), Tharp (1999: 233) and Kase (1996: 91).

complete randomness herald by the RWH: Mandelbrott (1963) warns about the existence of leptokurtic distributions; Lo & MacKinlay (1987) prove the non-randomness of stock prices based on the relationship between returns fluctuation and time; Sornette (2003) argues that markets dynamics can sometimes change creating "*pockets of predictability*" across diverse asset classes.

Concerning the EMH, it was first introduced by Eugene Fama in the early 1960's. According to Fama (1965b: 76) "*…in an efficient market at any point in time the actual price of a security will be a good estimate of its intrinsic value*". This implies that by the time new information reaches the market, all informed investors will act rationally upon it, making prices move towards a new intrinsic value. If there are fluctuations around this new value (defined by Black (1986) as "*noise*"), arbitrageurs will compete to move the price and adjust it accordingly. The main implication of the EMH is that there are no investment strategies capable of outperforming the market.

Still a pure technical analyst does not believe that either of these theories are a proper explanation of how markets behave, otherwise his work would be completely unnecessary. Instead, a pure technical analyst advocates Dow's Theory. Dow's Theory has developed by Charles Dow between 1900 and 1902, and is based on 6 principles[4]: Prices reflect all information, markets move based on trends, volume must confirm the trend, trends have 3 stages, trends remain in effect until a reversal signal occurs and, lastly, sector indexes must all point in the same direction as the trend. By embracing these principles a technical trader believes that it is possible to predict where the market is heading based on past behaviour. This premise challenges both the EMH and the RWH.

2.5. Behavioral Finance

The EMH was widely accepted until the 1990's, when a new approach called Behavioural Finance (BF) started to emerge. BF takes into consideration the fact that human beings are subject to cognitive bias and limitations when processing information and making decisions. Nowadays TA and BF are two sides of the same coin. Kirkpatrick and Dahlquist (2007: 49) write that "*Behavioural finance has become the theoretical basis for technical analysis. Investor sentiment and price anomalies, either as trends or patterns, have been the bulk of technical analysis study.*"

[4] Gomes da Silva (2013: 68)

A very well-known study on the behaviour of individuals is Kahneman and Tversky (1979), known as Prospect Theory. Kahneman and Tversky found irrational behaviour in the way people weight gains and losses. They found that people are very conscious and afraid of small losses and less encouraged by small gains. Furthermore they found that human are risk seeking when faced with potential losses and risk-averse and faced with potential gains. Kahneman and Tversky (1974) also prove the existence of other cognitive biases such as the anchoring effect, which causes investors to base decisions on irrelevant information.

An additional evidence of illogical behaviour is the disposition effect, which leads investors to be less willing to accept losses, but more willing to recognize gains. This conduct is irrational because investors should ideally cut their losses, in order to explore tax reductions on capital gains. However, as Odean (1998a) shows, this tax motivated selling occurs only in December. Throughout the rest of the year the disposition effect still subsists.

Research by Lai *et al.* (2010) argues that the disposition and the anchoring effect play a crucial role in the performance differential of several trading rules, in the Taiwanese stock market. They demonstrate that investors react differently to information on big-cap firms, as opposed to small-cap firms, as a result of the anchoring effect. Moreover their study highlights that both the disposition and information cascade effect translate into increased trading volume.

Other researches like Barber and Odean (2001), Gervais and Odean (2001) and Odean (1998b) tackle the issue of overconfidence, which is tightly related with managing risks. These studies provide some thought-provoking conclusions, like the fact that men are more prone to be overconfident than women, and the fact that most people become overconfident, as a resulting of taking too much credit for their own successes.

In addition, there are some curious anomalies that pushed forward the development of BF such as the January Effect. The January effect is a seasonal anomaly that causes stock prices to increase more in January than in any subsequent month. This occurrence suggests that the market is not efficient. However this anomaly is getting less and less noticeable, which is consistent with the premise of the EMH that any advantage would diminish and eventually self-destruct, when it is used by its adherents.

2.6. White's Reality Check

A key aspect in testing the forecasting ability of any technical indicator is to evaluate if the results that it produces have statistical support or, in contrast, are due to unforeseeable circumstances, such as luck. This issue is often referred to as data-snooping.

White (2000: 1097) refers that *"whenever a "good" forecasting model is obtained (...), there is always the danger that the observed good performance results not from actual forecasting ability, but instead just luck".*

From the set of statistical instruments available, the most well know test to compare the performance between two trading models is the *t-test*. Yet this test is known to have some weaknesses that can cast doubts over the results obtained (see section 3.5.2).

In order to address this issue, White (2000) , leaning on the works of Diebold and Mariano (1995), West (1996) and predominantly Politis and Romano (1994) , provided a framework (which we explain in detail in section 3.5.2) to control for data-snooping biases. This straightforward method, denominated White Reality Check (WRC), relies on bootstrap resampling and simulated returns, to test if a trading model has true superior predictive ability over a given benchmark, after taking into account the effect of other external factors, such as luck for instance.

White (2000) tested the methodology he himself developed, by applying it to the seminal work of Brock *et al*. (1992), and confirmed that the positive results obtained by the latter were robust to data snooping biases.

However, despite being a ground-breaking innovation, the work of White (2000) was challenged by other authors, who have drawn attention to some important aspects.

For example, Sullivan *et al*.(1997) by applying the WRC procedure to Brock *et al*. (1992) work, but this time extending the universe of trading rules to almost 8000 strategies, alert that data snooping bias can subsist due to survivorship bias. Therefore some trading rules are bound to outperform the benchmark strategy, even if they do not have real predictive power.

From this brief review of literature it is clear that the PSAR is not one of the primary technical indicators investors use to trade in the markets. Nonetheless its foundations and reasoning make it at least worth investigating. Therefore in this work we intend to implement the PSAR strategy and explore if the reasons for it to be disregarded are justifiable.

3. Methodology

In this section we provide a detailed explanation of how we implement all the relevant aspects of the different trading strategies. We start by defining which are the hypotheses subject to scrutiny and describe how we construct both the PSAR and the ADX. Then we focus on the assumptions we make when applying the diverse trading mechanism and explain how the resulting risks and returns are measured. Lastly we approach the issue of taxes and transaction costs and clarify how the results are statistically validated.

3.1. Hypothesis

As stated previously, the goal of this dissertation is to measure the effectiveness of the PSAR indicator as a trading strategy, as well as a stop-loss strategy, against the common assumption that financial assets should be bought and held. Hence there are three hypotheses subject to validation.

Hypothesis 1: *Using the PSAR as a trading strategy can improve returns and reduce risk, when compared to the BH strategy.*

In order to investigate this hypothesis, we apply the PSAR to the collected data, just as it is described by Wilder (1978: 9). This strategy forces investors to always be in the market, and adjust their positions according to the signals provided by the PSAR. Throughout the rest of the dissertation, this strategy will be referred as strategy 1, as it is the strategy used to validate hypothesis 1.

Hypothesis 2: *Using the PSAR as a stop-loss strategy can improve returns and reduce risk, when compared to the BH strategy.*

To test this hypothesis, we follow the BH approach as we normally would, but this time using the sell signals provided by the PSAR to exit the market, anticipating that it will go into a downtrend phase. The goal is thus to avoid times were investors potentially stand to lose money by holding the BH long position, due to a drop in asset prices. This strategy places investors out of the market until the downtrend is over, which is signalled when the PSAR generates a buy signal. Throughout the rest of this dissertation, this strategy will be referred as strategy 2, as it is the strategy applied to validate hypothesis 2.

Hypothesis 3: *Combining the PSAR with the ADX, can improve returns and reduce risk, when compared to the BH strategy.*

With the purpose of investigating this hypothesis, we apply the PSAR in the exact same way it is applied in hypothesis 1, but now including the ADX indicator as a trend measuring mechanism. The goal of doing so is to improve the quality of the trading signals, and avoid being "whipsawed" by unprofitable trades.

3.2. Technical Analysis Indicators

For the sake of making our argument as clear and easily understandable as possible, it is instrumental to describe how the PSAR and ADX behave. In the subsequent sections we provide a detailed explanation of how both indicators are built and applied.

3.2.1. Parabolic Stop-and-Reversal

The PSAR is a technical indicator that, accounting for past market action, specifies the price at which the current market trend is expected to reverse. As it refers to a price level, and since there are no negative prices, this indicator assumes always a positive value.

The mathematical formulation of the PSAR goes as equation (1) illustrates.

$$PSAR_{t+1} = PSAR_t + AF \times (EP - PSAR_t) \tag{1}$$

In equation (1), $PSAR_{t+1}$ stands for the value of the $PSAR$ at time $t + 1$, $PSAR_t$ stands for the value of $PSAR$ at time t, AF stands for Acceleration Factor and EP stands for Extreme Point.

The Extreme Point is the most favourable price level reached so far in the current trade. For instance, if investors hold a long position, the Extreme Point is highest price the asset reached up to that point. Conversely, if they hold a short position, the Extreme Point is the lowest price reached up to that point.

In turn, the $PSAR_{t+1}$ and $PSAR_t$ are the next day and today's observed stop-and-reversal price levels, respectively. These are the suggested levels at which positions are to be reversed in the future ($PSAR_{t+1}$), and the levels at which they should have been reversed in the past ($PSAR_t$), in case they were met.

As the predicted PSAR for time $t + 1$ is dependent from the PSAR at time t, there is the need to explain how to define the PSAR when $t = 0$.

Although Wilder suggests going back several weeks to a previous Extreme Point and then wait for the indicator to signal an entry in the direction of the reigning market trend, we do not apply this more complex approach. Instead we allow the PSAR to adjust to the market by itself. This is accomplished by setting the PSAR and the Extreme Point for $t = 0$ equal to the opening price and the lowest price of the first trading day in our data set, respectively. From that point onwards, we compute the indicator on a daily basis over 5 years before actually using it to start trading in 01/01/2000. This allows around 1250 days for the indicator to adjust autonomously to market conditions.

The last piece left to explain is the Acceleration Factor. By increasing its value every time a new Extreme Point is made, the Acceleration Factor is what grants the PSAR its ability of acting like a dynamic stop-loss. Its main purpose is to position the PSAR for $t + 1$ at safe levels, taking into consideration how the market is currently evolving. This is what prevents investors from being whipsawed by meaningless price movements. Wilder (1978:16) suggests setting the initial Acceleration Factor to 0.02 when a new trade (in either direction) is entered, and then increase it by 0.02 every time a new Extreme Point is reached. The Acceleration Factor must not, however, exceed the maximum value of 0.2.

Although the computation of the PSAR is straightforward, it still has to comply with one important rule: The PSAR for $t + 1$ must never step into either today's range or yesterday's range. Therefore if investors have a long position, the predicted PSAR is required to be below today's and yesterday's low, and above today's and yesterday's highs if they hold a short position.

This must be abided to allow the trade enough room to move without incurring in too much risk of hitting a stop-loss level prematurely.

However if the predicted PSAR for $t + 1$ violates this rule, investors need to make a slight adjustment. If they hold a long position, they must choose the smaller between yesterday's and today's lowest price as the predicted PSAR $t + 1$. Conversely, if they hold a short position, they must choose between yesterdays and today's highest price as the PSAR for $t + 1$ (see Figure 4 and Figure 5, respectively).

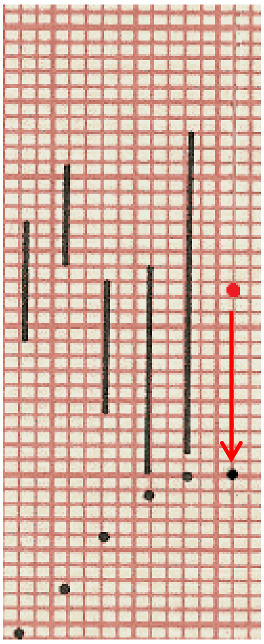

Figure 4 - PSAR adjustment for t+1 if investors are long
Source: New Concepts in Technical Trading Systems - Page 12

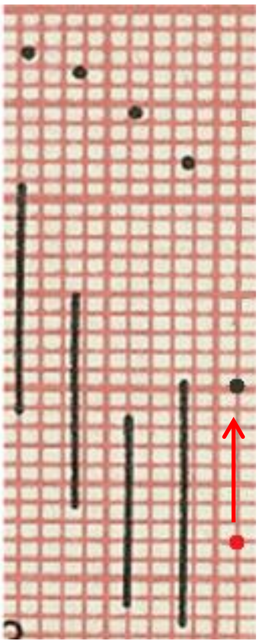

Figure 5 - PSAR adjustment for t+1 if investors are short
Source: New Concepts in Technical Trading Systems - Page 12

In section 8.1 we provide an illustration of how the PSAR is computed and implemented.

3.2.2. Average Directional Index

In order to make the signals generated by the PSAR more accurate, Wilder suggests using it alongside with the ADX. This indicator seeks to help investors defining whether an asset is in a trending phase or in a ranging phase. Despite being very easy to interpret, the computation of the ADX has some specificities that must be described. We start by introducing two base concepts: Directional Movement and True Range (henceforth DM and TR, respectively).

The DM[5] is the largest part of today's range that is outside yesterday's range. It measures how much prices moved beyond the limits of the previous day trading range, either up or down. DM can be considered either positive (+DM), if a new high has made when moving outside yesterday's range (Figure 6), or negative (-DM), if a new low has made when moving outside yesterday's range (Figure 7). If prices do not move outside yesterday's range the DM is considered to be 0.

There are still two additional features that characterize the DM. The first is that, by construction, it always assumes a positive value, even when considering a down move. The second is that the DM is classified strictly as +DM or –DM. On any given day there cannot be simultaneously two types of DM.

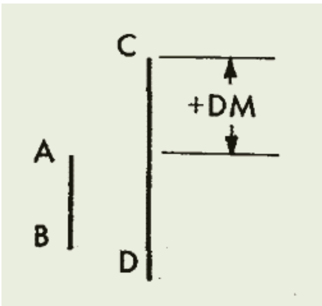

Figure 6 - +DM
Source: New Concepts in Technical Trading Systems - Page 35

[5] DM is always expressed in the same units as the underlying asset.

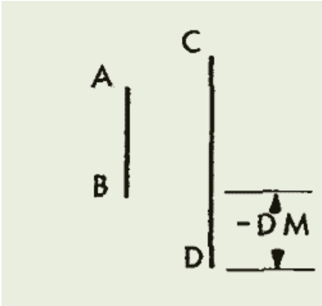

Figure 7 - -DM
Source: New Concepts in Technical Trading Systems – Page 35

Even though the DM is fundamental in comprehending the mechanics of the ADX, the truth is that, by itself, DM is meaningless. For the DM to be meaningful it must be expressed as a function of a range. Or, as Wilder (1978: 36) writes, a True Range.

The difference between a "Range" and a "True Range" is that the latter measures how much prices actually moved from one trading day to the other, taking into account price gaps. It is not unusual in financial markets to have gaps between yesterday's closing price and today's opening price. These gaps can develop, for example, if a company presents results estimates or a significant macroeconomic event happens after the market closes. Therefore the TR for a given day, which like the DM is always a positive number, is the largest distance between:

- Today's high and today's low (D1)
- Today's high and yesterday's close (D2)
- Today's low and yesterday's close (D3)

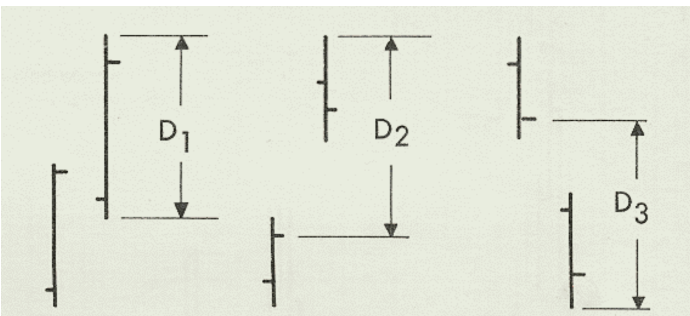

Figure 8 - Possible combinations for a given day TR
Source: New Concepts in Technical Trading Systems - Page 21

In order to express the DM relatively to a TR, we simply divide both, obtaining the Directional Indicator (DI). The DI depicts the bull and bear momentum for a given day, as a percentage of how much prices have actually moved. The mathematical formulation of the DI goes as equations (2) and (3) display:

$$+DI_1 = \frac{+DM_1}{TR_1} \tag{2}$$

$$-DI_1 = \frac{-DM_1}{TR_1} \tag{3}$$

In equations (2) and (3), the $+DI_1$ and $-DI_1$ stand for the DI for one day, and DM_1 and TR_1 stand for the directional movement and true range for that same day. It is important to note that, in the previous equation, the minus signals are not to be interpreted as a mathematical operator, but instead as an indication of downward DM.

Although the DI_1 provides a clue about which strength dominated the market on a given day, a one day period is not enough time to determine with certainty which strength is dominating in the long run. Therefore an extended horizon for the DI is needed. Wilder (1978: 37) suggests using a period of 14 days for the computation of the DI and its components, claiming that it represents "*an average half-cycle period* ". As we follow Wilder's approach in our analysis, we have also used 14 days. The DI for 14 days is computed according to equations (4) and (5).

$$+DI_{14} = \frac{\sum_{i=1}^{14} +DM_i}{\sum_{i=1}^{14} TR_i} \times 100 \tag{4}$$

$$-DI_{14} = \frac{\sum_{i=1}^{14} -DM_i}{\sum_{i=1}^{14} TR_i} \times 100 \tag{5}$$

The interpretation of the DI_{14} is essentially the same as the DI_1, but for a larger time-span.

As equations (4) and (5) illustrate, for computing the DI_{14} investors need to have data from the previous 14 days available. In addition they need also to have the IT tools to analyze that same data. Although nowadays with the advent of computer power and information this is no problem, in 1978, when Wilder developed the ADX, it was a limitation. Therefore, in order to make the calculations nimbler, Wilder defined an alternative way to compute the DI_{14}. This method is called the accumulation technique. The main advantage of incorporating this technique in this dissertation as not to do with facilitating the computation of the ADX, since nowadays there is more than enough computer power to address this issue. The advantage lies instead, as Wilder (1978: 37) refers, in incorporating a smoothing effect on the DM.

By using the accumulation technique, the DM_{14} and TR_{14} are calculated as equations (6), (7) and (8) display.

$$Today's\ {+DM}_{14} = Previous\ {+DM}_{14} - \frac{Previous\ {+DM}_{14}}{14} + Today's\ DM_1 \tag{6}$$

$$Today's\ {-DM}_{14} = Previous\ {-DM}_{14} - \frac{Previous\ {-DM}_{14}}{14} + Today's\ DM_1 \tag{7}$$

$$Today's\ TR_{14} = Previous\ TR_{14} - \frac{Previous\ TR_{14}}{14} + Today's\ TR_1 \tag{8}$$

Despite the DI being an innovation in the way price movements are perceived in financial markets, the major breakthrough of Wilder's work is, as he describes, being able to establish a connection between $-\mathrm{DI}_{14}$ and $+\mathrm{DI}_{14}$.

In fact, Wilder showed that the greater the absolute difference between $+\mathrm{DI}_{14}$ and $-\mathrm{DI}_{14}$, the stronger the trend in place. Conversely, if this difference is small, it indicates that there is no leading trend, and the market is experiencing a period of sideways action. In this scenario it is not wise to use trading systems that seek to profit from the existence of a trend, like the PSAR.

The relation between the absolute difference of $-\mathrm{DI}_{14}$ and $+\mathrm{DI}_{14}$ leads to the Directional Movement Index (DX). The DX quantifies how much of all momentum existing in the market is truly able of making prices move significantly and is computed according to equation (9).

$$DX = \frac{|-DI_{14} - +DI_{14}|}{+DI_{14} + -DI_{14}} \tag{9}$$

The output of equation (9) is always a positive number, fluctuating between 0 and 100. Consequently, the higher the value of the DX, the stronger the trend dominating the market at that point. Notice, however, that for the DX it is indifferent whether prices move up or down, as it does not differentiate upwards price movements from downwards price movements. If prices are moving swiftly in any direction, the DX will always increase.

Finally we reach the ADX, which is no more than an average of the DX. The process of averaging the DX helps to smooth out more irregular actions, which can occur in periods of increased volatility. Wilder (1978: 40) states that the period for determining the DX has to be at least twice the period used to compute the DI14, and suggest using an average of 14 days to compute the first ADX. Equation (10) illustrates how the first ADX is computed.

$$ADX_1 = \frac{\sum_{i=1}^{14} +DX_i}{14} \tag{10}$$

To compute the subsequent ADX the accumulation technique is once again used, as equation (11) displays.

$$Today's\ ADX = \frac{Previous\ ADX \times 13 + Today's\ DX}{14} \tag{11}$$

When using the ADX, there is only one rule investors are suggested to follow: enter new trades only if the ADX is above 25. This is the case because Wilder considers this to be the threshold for a trending market. Any ADX value below 25 means that the market is moving sideways and therefore trend following systems should be avoided. This is also the threshold for a strong trending market we use in this analysis.

3.3. Trading Strategies Implementation, Transaction Costs and Taxes

In this section we refer the assumptions we did concerning the implementation of the different trading strategies, as well as transaction costs and taxes. We start by focusing on the trading strategies and then we proceed to transaction costs and taxes.

3.3.1. Trading Strategies Implementation

In order to test the usefulness of strategies 1, 2 and 3, we implement all indicators and trading strategies using Microsoft Excel software. The main concern in building the strategies from scratch is to avoid the misuse of data.

If investors trade in real time, they can only base their decisions in past and present information. Nevertheless, by testing the strategies in an *ex-post* basis, all the information regarding the evolution of the underlying assets is known beforehand. Thus it is vital to make the analysis as robust as possible to the criticism that, following our theoretical model, investors are basing their decisions on information they could not possibly know. In that end in mind, we apply the PSAR and the ADX lagged by one day for all the strategies tested.

Another key aspect we must make clear is the reasoning behind each of the 4 strategies tested and how they are put into practice. Although the primary motivation of any of the 4 trading strategies is to generate positive returns, their goals go beyond that. For that reason there are certain particularities regarding the way these strategies trade that must be addressed.

In the following paragraphs we focus on this issue, starting by the BH strategy.

The BH is a passive strategy par excellence. It relies on the assumption that no other trading strategies are able to outperform the market and therefore doing something other than buying the asset and holding it is pointless. This strategy is in line with the assumptions of the EMH and if none of the remaining 3 trading strategies can outperform it, it is a sign that this premise holds.

Being the BH the most basic strategy any investor can follow is also the easiest to implement: We simply assume investors buy the asset at the opening price of the first trading day and sell it at the closing price of the last trading day.

To what concerns the remaining 3 strategies, the motivation behind them is not as straightforward as the BH.

The reasoning behind strategy 1, is trying to predict whether an asset is going to move up or down based on the PSAR readings. The goal is to position investors accordingly in order to profit from buying or selling the asset at the right time. This strategy allows investors to profit in each and every day and not only when price increases, like the BH does. This strategy assumes investors are always in the market, either buying or selling, and thus there are no outdays[6] from applying it.

To put this strategy in practice, we simply assume investors follow the signals given by the PSAR closely and reverse their positions whenever the signal contrary to the position they currently hold emerges. Therefore if they hold a long position and a sell signal appears, they will dispose their long position and change to a short position. If a buy signal emerges and investors hold a short position, they do exactly the opposite.

Whenever investors need to change for one type of position to the other we assume they exit the old trade and enter the new one entered at the opening price for the next trading day, as they could simply leave a pending order overnight to be executed the minute the market opens.

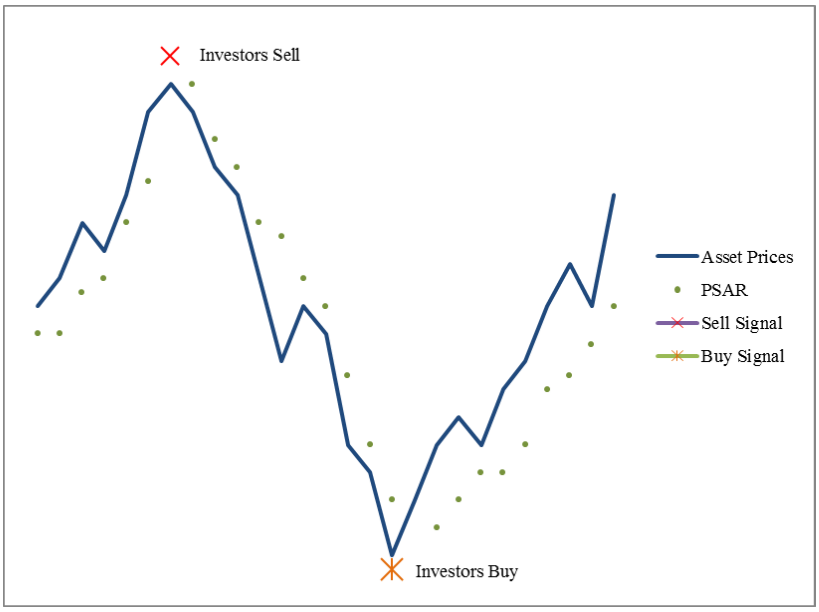

Figure 9 - Trading scheme for Strategy 1
Source: The author

[6] In the context of this dissertation outdays are the days were investors do not hold any position.

Regarding strategy 2, the goal is now to investigate if PSAR prevents investors from losing money when asset prices are expected to fall. This strategy seeks to keep to a minimum the negative returns that destroy the profitability of the BH strategy by using the PSAR as a stop-loss strategy.

With that end in mind, we assume investors follow the signals generated by the PSAR, with the exception that now when a sell signals emerges investors do not reverse their positions, but instead close them. Hence in this strategy the number of outdays is different from zero. Once again we assume investors enter or exit their positions at the opening price of the next trading day, just like in strategy 1.

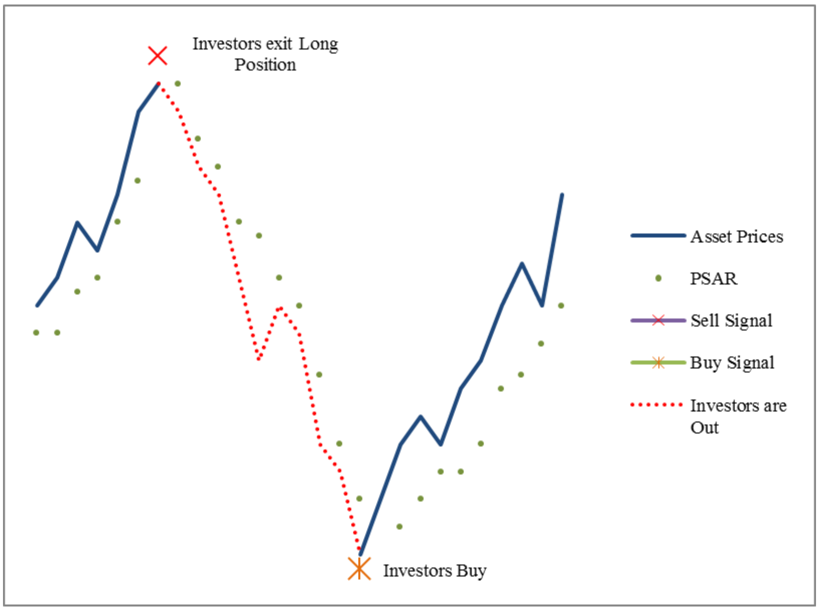

Figure 10 - Trading scheme for Strategy 2
Source: The author

In respect to strategy 3, the motivation behind it is the same as for strategy 1. However now, by using the ADX to filter out times were the market is trendless, the signals generated by the PSAR are expected to improve, thus making returns also better.

Implementing this strategy is very similar to implementing strategy 1, with a minor difference in the way trades are entered and exited. For strategy 3, we assume a new trade is entered only when the PSAR generates a signal and the ADX confirms that there is a strong enough trend to back up that signal (i.e. the ADX is above 25). On the other hand, investors exit their position when the ADX falls below 25, because it does not make sense to rely on a trend following indicator like the PSAR when there is no trend in place. For that reason the number of outdays in this strategy is also different from zero. Once again we assume investors enter the market the day after a signal occurred.

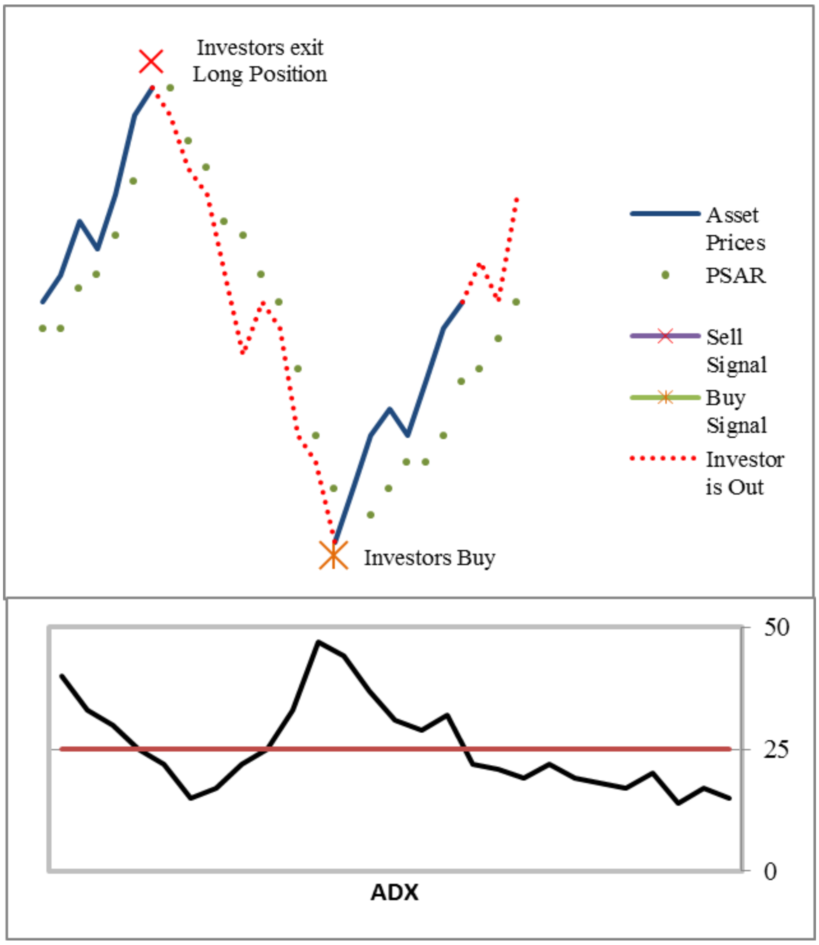

Figure 11 - Trading scheme for Strategy 3
Source: The author

3.3.2. Transaction Costs and Taxes

Several prominent authors have opposing views about transaction costs. While some argue that transactions costs erase all the profits from TA (Bessembinder and Chan (1997); Ready (1997); Fama and Blume (1966)), others find evidence of profitability after accounting for these costs (Caginalp and Laurent (1998); Brock *et al.*, (1992); Alexander, (1961)). However as Horton (2009: 288) points out "…*transactions costs have declined over the past few decades and must therefore be modelled at a very micro level if they are to be modelled accurately.*". For that reason, correctly accounting for transactions costs is a complex procedure, since our data set is 15 years long and because the different assets have different transaction costs that have changed through time.

Furthermore, the non-inclusion of transaction costs does not change the outcome of our analysis. As Aronson (2007:34) argues, not including transactions costs in the analysis can make clear if the strategies have predictive power or not, from an EMH perspective. From that perspective, a strategy that proves itself profitable based on the analysis of previous data would challenge the EMH and would act as evidence against it. As such, we chose not to include transactions costs in our analysis.

Concerning taxes, these would affect both the PSAR strategies and the BH and therefore there is no clear advantage of one strategy over the other. Besides the aforementioned instruments are traded in different countries, each with its own tax-system, which makes the task of properly accounting for taxes very difficult. Hence we do not consider them.

Lastly it is important to make clear some practical issues about the transactions itselves. We assume that there are no slippage costs, since the selected assets are highly liquid and thus orders are filled at the designated price. Moreover, when investors are not actively invested in the market, which happens in the case of strategies 2 and 3, we assume the money is not invested elsewhere so as not to distort the true rate of return of the strategy. We use stock prices adjusted for dividends and stock splits.

3.4. Characterization, Returns and Risk Measurements

In this section we refer the tools we use to allow comparisons between strategies and explain how we include them in our analysis. We start by mentioning how we characterize each strategy and then proceed to explain the metrics we use to compare returns and risk amongst them.

3.4.1. Characterization of each strategy

To characterize the inner workings of each strategy, we rely on 4 important measures: the number of trading days, the amount of buy and sell signals that occurred on those trading days, the percentage of correct and incorrect signals and the amount of days investor did not trade (outdays).

Although the interpretation of these numbers is straightforward, there are two aspects about them which are not immediately evident to the naked eye and need to be further addressed.

The first aspect worth mentioning is related with the number of signals for strategies 1 and 2. Although the reaction to a trading signal is different for each strategy (the first reverses the position, the other closes it) the signals generated for both are exactly the same, because both rely on the PSAR indicator and follow its daily observations. Thus the number of buy and sell signals is the same for both strategies.

The second key aspect is how to evaluate if a signal is profitable or unprofitable. With that end in sight, we define a profitable buy signal as a signal that translates an increase in the price of the underlying asset and consequently a positive return. On the other hand a profitable sell signal is a signal that translates a decrease in the price of the underlying asset and consequently a negative return.

Conversely, unprofitable signals are exactly the opposite: buy signals that translate a decrease in the price of the underlying asset and sell signals that translate an increase in the price of the underlying asset.

Keeping this in mind, note that the number of profitable and unprofitable buy signals for strategy 1 is always the same as for strategy 2, because the interpretation of what makes a signal profitable or unprofitable is the same. However in the case of sell signals this is not so because both signals are analogous: A profitable sell signal in strategy 1 (which represents a decrease in the price of the underlying asset) translates into an unprofitable sell signal in strategy 2, because investors would be better off if they followed the correct sell signal, instead of being out of the market. For that reason the number of profitable and unprofitable sell signals for strategies 1 and 2 is always mirrored.

After defining what makes a signal profitable or unprofitable, we are able to express the amount of profitable signals as a percentage of the total amount of signals. This percentage is named Hit Ratio, and it is computed according to equation (12). The Hit Ratio is a central piece in every good trading mechanism because it measures how consistent are the results obtained. As an example, a strategy that yields remarkable returns, but at the same time has an Hit Ratio of 10% is very risky and of no real value.

$$Hit\ ratio = \frac{Profitable\ buy\ or\ sell\ signals}{Total\ number\ of\ signals} \tag{12}$$

3.4.2. Returns

In order to determine how good are the results obtained from applying the different trading strategies, we compute daily returns by considering the logarithmic variation of closing prices, as equation (13) depicts.

$$Return\ day\ t = \ln\left(\frac{Closing\ Price\ day\ t}{Closing\ Price\ day\ t-1}\right) \tag{13}$$

When there is the need to close a position at the opening price of the next trading day, returns are computed according to equation (14).

$$Return\ day\ t = \ln\left(\frac{Opening\ Price\ day\ t}{Closing\ Price\ day\ t-1}\right) \tag{14}$$

Average returns for the entire holding period are calculated as equation (15) shows.

$$Average\ Return = \frac{\sum_{i=1}^{n} Return\ day\ n}{Number\ of\ Days} \tag{15}$$

Still it is important to note that for each trading strategy we present average returns from following buy and sell signals separately. This separation is a way of translating more accurately which type of signal yields better returns.

If the average of the full set of long and short returns mixed together is considered as the true average return of a given strategy, one does not take into account the fact that the PSAR positions investors either long or short. Thus averaging the full set of returns will not accurately illustrate the true potential of the trading strategy. Hence the need of separating both type of returns. This methodology was also applied by Brock *et al.*(1992) in his seminal work. Equation (16) shows how separated returns are computed.

$$Average\ Return_{b/s} = \frac{\sum_{i=1}^{n} Return\ day\ n_{b/s}}{Number\ of\ Days\ following\ signal\ _{b/s}} \qquad (16)$$

Now that returns are clearly defined, the challenge lies in how to compare strategies as a whole, since they have different types of returns. This challenge comes from the fact that it is impossible to compare returns from sell signals (that are expressed by a negative number) with returns from buy signals (that are expressed by a positive number) by simply adding both together. To overcome this issue we have analysed them separately, focusing on the absolute value of returns. Therefore the best strategy is the one that shows, for long returns, a higher absolute return when compared to the BH and for short returns the best strategy is the one that shows, not only a higher absolute value of returns when compared to the BH, but also returns with a negative sign, thus translating a profit from a short position.

If a strategy happens to be better than the BH for one type of signal, but worse for the other type, we deem the strategy unprofitable, as we are only concerned with trading strategies that are strictly better than the BH, under any circumstance.

3.4.3. Risk and volatility measures

Regarding risk, the most natural choice is to use the variance of returns to gauge volatility. However by applying the variance to the complete series of returns, we face the same issue as we did before: one does not take into account that technical indicators trigger not only buy signals, but also sells signals. To overcome this issue, we work out separately the variance of returns from buy signals and from sell signals, as equation (17) illustrates.

$$\sigma_{b/s}^2 = \frac{\sum_{i=1}^{N}(x_i - \mu)^2}{N_{b/s}} \qquad (17)$$

In equation (17), $N_{b/s}$ stands for the number of days following buy or sell signals, μ stands for the average return for a given type of signal and x_i stands for the i_{th} observation of daily returns.

Although the variance on its own provides a good idea of how strategies compare to one another, it does not allow taking into account if strategies that take in more risk also provide extra returns. This information is particularly important because it helps investors distinguishing between strategies that can incorporate "good" risk from strategies that simply increase returns because they increase risk meaninglessly.

To overcome this issue, we apply the Return to Risk Ratio (R3). This simple computation has the virtue of clarifying if the returns from following the different strategies are better than the BH when risk is accounted for.

Since the returns from short positions have a negative sign, we adjusted the interpretation of R3 for absolute values, just like we did for returns. Keeping this in mind, for the R3 for buy signals to be better than the BH, we require it to be a positive number and greater in absolute value than the BH's R3. For sell signals, we require it to be a negative value (as now it represents the profit from a short position) and greater in absolute value than the BH's R3.

Equation (18) illustrates how the Risk Return Ratio is computed.

$$Return\ to\ Risk\ Ratio\ (R3) = \frac{Average\ Return_{b/s}}{\sigma^2_{b/s}} \tag{18}$$

3.5. Statistical Validation of Results

To better describe the performance and robustness of the results obtained, we focus our attention on inferential statistics. In this section we present the methodologies we use for that purpose.

3.5.1. *T-test*

In order to compare the returns from different strategies we rely on a two-tailed *t-test*. Since the sample size is large enough it is possible, by the central limit theorem, to assume the normality of returns and overcome one of the limitations of the *t-test*. To apply the *t-test* we follow the methodology introduced by Brock *et al*.(1992). The advantage of using this type of *t-test* is that it allows evaluating the quality of the results obtained, by separating returns from long positions and returns from short positions. Moreover it allows testing if the strategies show signs of being able to correctly time the market, by analysing if the spread between buy and sell signals is statistically significant.

To test if buy and sell signals outperform the results of the BH, we consider form two null hypothesis. The first hypothesis is that the average return from following buy and sell signals is not statistically different from the average return of the BH, as equation (19) depicts. If this hypothesis holds, we cannot deny that the excess mean return from following buy or sell signals is different from zero and therefore it is unclear whether the strategies are actually profitable or not.

$$H_{0:}\bar{r}_{b(s)} - \bar{r} = 0 \tag{19}$$

On the other hand rejecting this null hypothesis proves that the average returns from the trading strategies actually outperform the market, as equation (20) shows.

$$H_{A:}\bar{r}_{b(s)} - \bar{r} \neq 0 \tag{20}$$

To access the validity of the hypotheses stated in equations (19) and (20), we compute the following test statistic, with standardized normal distribution.

$$t = \frac{\bar{r}_{b(s)} - \bar{r}}{\sqrt{\frac{\sigma^2{}_{b(s)}}{N_{b(s)}} + \frac{\sigma^2}{N}}}, \tag{21}$$

In equation (21), $\bar{r}_{b(s)}$ is the average return from following buy and sell signals, $\bar{r}$ is the average return from following the BH strategy, $\sigma^2{}_{b(s)}$ is the returns variance of buy and sell signals, σ^2 is the returns variance of the BH strategy, $N_{b(s)}$ is the number of days following buy and sell signals and lastly N is the number of days following the BH strategy. It is also assumed that returns from the two different strategies are independent.

The second aspect we evaluate is if the average return coming from buy signals is significantly different from the one that come from sell signals. The purpose of testing the buy-sell spread is to check if the trading rules actually provide good overall results. A significantly positive buy-sell spread indicates that the rules generate valuable signals, meaning that the strategies can correctly distinguish moments when to buy and when to sell. In this scenario the null and alternative hypotheses are:

$$H_{0:}\bar{r}_b - \bar{r}_s = 0 \tag{22}$$

$$H_{A:}\bar{r}_b - \bar{r}_s \neq 0 \tag{23}$$

To assess the validity of these hypotheses stated in equations (22) and (23), we rely on following test statistic:

$$t = \frac{\bar{r}_b - \bar{r}_s}{\sqrt{\frac{\sigma^2{}_b}{N_b} + \frac{\sigma^2{}_s}{N_s}}} \tag{24}$$

In equation (24), $\bar{r}_b$ is the average return from following buy signals, $\bar{r}_s$ is the average return from following sell signals, $\sigma^2{}_b$ is the variance of returns from buy signals, $\sigma^2{}_s$ is the variance of returns from sell signals and lastly N_b and N_s is the number of days following buy and sell signals. Returns from both strategies are assumed independent.

We reject all the null hypothesis presented in this section if the absolute value of the test statistic exceeds the critical value of $t_{\frac{\alpha}{2};N}$, where α is the significance level, which we set to 1.0%, and N the number of degrees of freedom, which correspond to the number of daily observations for each asset.

3.5.2. White RC

In addition to the *t-test*, we apply a bootstrapping methodology developed by White (2000) called the White Reality Check. This sampling technique relies on stationary bootstrapping and has several advantages when compared to the *t-test*, such as taking into consideration dependencies across trading rules and not making distributional assumptions.

The purpose of the WRC is to detect data snooping by assessing if the trading strategies outperform the BH due to pure luck, or if they have in fact predictive power.

To do so, consider a trading method (let us call it A), that predicts the position the investor should hold for the next trading day, like the PSAR does. Testing if trading method A is better than the benchmark strategy (the BH in our analysis) implies determining how bigger the returns of that trading method are in comparison to the benchmark. Translating the excess return of trading method A over the benchmark mathematically results in equation (25).

$$\widehat{R_{excess}}^{t} = \log(1 + y^t S_A) - \log(1 + y^t S_B) \tag{25}$$

In equation(25), t refers to a given point time , the subscript A and B denote the trading strategy and the benchmark strategy respectively, S denotes the three possible types of trading signals (1 for Long, -1 for Short, 0 for neutral) and y denotes the relative variation in asset prices , computed according to equation (26).

$$y^t = \frac{v^t - v^{t-1}}{v^t} \tag{26}$$

In equation (26), v^t and v^{t-1} denote the price of the underlying asset at time t and $t - 1$, respectively.

Furthermore note that:

$$\log(1 + y^t S_A) = \log\left(\frac{v^t}{v^{t-1}}\right) \tag{27}$$

Following equation (25), the return for time t can be simplified and written as:

$$r_i^t = \log(1 + y^t S_i)\,, \qquad i = A, B \tag{28}$$

In turn the excess return of the trading method A over the benchmark strategy can also be simplified and rewritten as:

$$\widehat{R_{excess}}^{\,t} = r_A^t - r_B^t \tag{29}$$

Let us now consider a statistic that represents the average excess return of trading strategy A over the benchmark strategy, for the n observations in the original time series, such as equation (30) illustrates.

$$\bar{R}_{excess} = \frac{1}{n}\sum_{t=0}^{n} \widehat{R_{excess}}^{\,t} \tag{30}$$

$$= \frac{1}{n}\left(\sum_{t=0}^{n} r_A^t - \sum_{t=0}^{n} r_B^t\right)$$

$$= \bar{r}_A - \bar{r}_B$$

Suppose now we want to test the statistical significance of $\overline{\mathrm{R}}_{\mathrm{excess}}$, ie, we want to test if trading strategy A yields positive average excess returns when compared to the benchmark method. For that purpose we take the following null hypothesis into consideration.

$$H_0: E[R_{excess}] \leq 0 \tag{31}$$

Rejecting the null hypothesis in equation (31) implies that there is in fact evidence that trading method A is superior to the benchmark strategy, even after controlling for data snooping biases.

The main challenge in validating the aforementioned hypothesis lies in the fact that it is not possible to get a large sample of $\bar{R}_{excess}$ using real data. This is the case because there is just only one observation of the true $\bar{R}_{excess}$ for a given time frame. To overcome this aspect and generate more observations of $\bar{R}_{excess}$, White (2000) suggest using the stationary bootstrapping method of Politis and Romano (1994), which we explain in detail in section 3.5.3.

By applying Politis and Romano method, it is possible to generate an approximation of the real distribution of $\bar{R}_{excess}$. If the null hypothesis in equation (31) is rejected it is a sign that, even after accounting for a large number of simulations, the excess return of the trading strategy can be attributed to its own merits and not to some other external factors.

The expression of the bootstrapped average excess return of method A over the benchmark is depicted in equation (32).

$$n^{1/2}(\,\bar{R}_{excess} - E[R_{excess}]) \approx n^{1/2}(\,\bar{R}^{*}_{excess} - \bar{R}_{excess}) \tag{32}$$

In equation (32), $\overline{\mathrm{R}}^{*}_{excess}$ is the bootstrapped average excess return of the trading method A over the benchmark method.

By repeating the bootstrap resampling process j times, one can get a sample of bootstrapped excess returns large enough to generate an approximation of the true distribution of $\bar{R}_{excess}$, as equation (33) illustrates. In our analysis we use 500 bootstraps, which is the same number used by Sullivan *et al*. (1997).

$$\bar{R}_{excess} \approx \bar{\mathrm{R}}^{*}_{excess,j} = \frac{1}{n}\sum_{t=0}^{n} \widehat{\mathrm{R}_{\mathrm{excess,j}}}^{\mathrm{t}} = \bar{r}_{A,j} - \bar{r}_{B,j}\,, \qquad j = 1,2 \ldots,500 \qquad (33)$$

Denoting the original data set by $\mathrm{j} = 0$ we now define:

$$\bar{V}_{A,0} = n^{1/2}\bar{\mathrm{R}}_{\mathrm{excess,0}} \qquad (34)$$

In equation (34), $\bar{V}_{A,0}$ denotes the average excess return of trading strategy A in the original data set. Furthermore we define:

$$\bar{V}^{*}_{A,j} = n^{1/2}\left(\bar{\mathrm{R}}^{*}_{\mathrm{excess,j}} - \bar{\mathrm{R}}_{\mathrm{excess,0}}\right), \qquad j = 1,2 \ldots,500 \qquad (35)$$

In equation (35), $\bar{\mathrm{V}}^{*}_{\mathrm{A,j}}$ stands for the series of average bootstrapped excess returns over the original excess return for *j* bootstraps.

Testing the null hypothesis of no excess returns in equation (31) is equivalent to determine if $\bar{V}^{*}_{A,j} \geq \bar{\mathrm{V}}_{\mathrm{A,0}}$. Thus the hypothesis can only be rejected if $\bar{\mathrm{V}}_{\mathrm{A,0}}$ is located at the right tail of the distribution of $\bar{V}^{*}_{A,j}$, meaning the original excess return of strategy A over the benchmark is significantly larger than the great majority of bootstrap excess returns.

The p-value is obtained by simply subtracting one minus the percentile of $\bar{V}^{*}_{A,j}$ having the value of $\bar{\mathrm{V}}_{\mathrm{A,0}}$. To determine where this percentile is located we sort $\bar{V}^{*}_{A,j}$ as $\bar{V}^{*}_{A,(1)} < \bar{V}^{*}_{A,(2)} < \bar{V}^{*}_{A,(N)}$ and find M such that $\bar{V}^{*}_{A,(M)} < \bar{\mathrm{V}}_{\mathrm{A,(0)}} < \bar{V}^{*}_{A,(M+1)}$. The p-value is given by $\mathrm{p} = 1 - \frac{\mathrm{M}}{\mathrm{N}}$.

3.5.3. Stationary Bootstrapping – The back bone of White's Reality Check

Bootstrapping procedures are statistical tools that allow estimating non-parametrically certain properties of a statistic of interest. The use of these sort of procedures is very common in the field of finance, but it is also widespread across other sciences[7].

White's Reality Check relies on a particular bootstrapping method named stationary bootstrapping, which was developed by Politis and Romano. In this section we explain in detail the steps we take to put this methodology in practice.

Stationary bootstrapping, like any other bootstrapping method, consists in generating a new set of observations, taking as a starting point the original set of observations. However there is a key difference in the way stationary bootstrapping generates these new observations. While classic bootstrapping methods generate all new observations in one large group, the stationary bootstrapping does that by creating subsets of that one large group and later puts them together.

As an example, consider two bootstrapping methods, a classic bootstrapping and a stationary bootstrapping, designed to generate 100 new observations of an original data set. While the classical method generates 100 new observations in one block of 100 observations, the stationary bootstrapping method proceeds differently. First it generates a smaller block of, for example, 14 observations, followed by a block of 20, and so on, until 100 new observations are put together. This unique feature guarantees that the simulated series are stationary, as long as the original series are stationary.

In the context of this dissertation, a block of observations is the series of random excess returns over the BH, as illustrated previously in equation (29). Moreover we guarantee that the generated blocks of excess returns are stationary due to the fact that logarithmic returns are, by construction, stationary.

However, despite the simulated excess returns being generated in blocks of observations of variable length, the length of these blocks must converge to a fixed mean value. Politis and Romano achieve that goal by imposing the average length of the blocks to be equal to the expected value of a geometric distribution.

[7] See for example Efron (1982) and Kunsch (1989).

Equations (36) and (37) illustrate the probability density function and the expected value of a geometric distribution.

$$Prob(X = k) = (1 - q)^{k-1} \times q, \qquad for\ k = 1,2 \dots, N \tag{36}$$

$$E[X] = \frac{1}{q} \tag{37}$$

The main issue now is how to choose the value of q. This is particularly important because q reflects the degree of dependency in the generated series. A high value of q reflects low dependency in the series, while a low value of q implies high dependency in the series.

Politis and Romano argue that the optimal value of q is in the order of $n^{-\frac{1}{3}}$, as it minimizes the mean square error of the estimated variance. On average, the time-series we use has 3823 observations, which sets q in the order of 0,06. This translates into a 16 day dependency from previous returns.

Below, we list the step by step process we take to apply the stationary bootstrapping method.

1. Pick a number i at random from 1 to n, then pick the i-th element in the original series (i.e., the i-th original excess return over the benchmark) to be the first element in the simulated series
2. Pick a number z at random from a uniform distribution between 0 and 1
   - 2.1. If $z > q$, chose the next element in the original time series ($i + 1$) to be the next element in the bootstrapped time series. If $i = n$, the next element in the bootstrapped series is the first element in the original series
   - 2.2. If $Z <= q$, repeat step 1, selecting the i-th element as the next element in the bootstrapped series
3. Repeat step 2 until the bootstrapped series has n elements

To keep computations manageable we chose to perform 500 bootstraps. Nevertheless each of these 500 bootstraps has on average 3823 observations, which adds up to around 1.910.000 simulated excess returns.

4. Data

We test the PSAR indicator on a set of 10 financial assets, during a period of 15 years ranging from 01/01/2000 to 01/01/2015. The selected assets are the EUR/USD and USD/JPY exchange-rates; the iShares MSCI Japan, the SPDR SP500 and iShares EURO STOXX 50 UCITS ETF's; the common stock of Toyota, Portugal Telecom and JP Morgan Chase; and lastly Gold and Brent. The selected assets are highly liquid and representative of several markets and industries. By diversifying across different assets we aim to overcome possible criticisms regarding data-snooping and to generalize results as far as possible. Moreover, the selected time interval allows testing the PSAR under various market conditions, like the 2008 financial crisis. Table 1 summarizes the number of observations collected for each asset. All the data was obtained from Bloomberg platform.

Asset	Nº Observations
Brent	3832
EUR/USD	3913
JP Morgan Chase	3773
MSCI Japan ETF	3773
Portugal Telecom	3814
S&P500 SPDR ETF	3773
Eurostoxx 50	3841
Toyota	3684
USD/JPY	3913
Gold	3911
Average	3823

Table 1 - Number of observations for each asset
Source: The author

5. Empirical Results

In this section we present the results obtained from applying the PSAR based strategies. Firstly, we illustrate the inner workings of each strategy, by analysing the accuracy of the different type of trading signals and how frequently they occur. In second place, we approach the issue of returns and volatilities and how they compare to the BH. Finally we present the breakdown of the statistical robustness. Sub Section 5.1 is dedicated to strategies 1 and 2, and sub-section 5.2 is dedicated to strategy 3.

5.1. Strategy 1 & Strategy 2

5.1.1. Characterization

As mentioned in section 3.1, the PSAR indicator is used on a standalone basis to test hypothesis 1 and hypothesis 2, by means of strategies 1 and 2 respectively. Thus, as both strategies rely on the interpretation of the same PSAR signals to be validated, the analysis is done jointly for both.

Table 2 and Table 3 illustrate the average results for the set of 10 assets. The results for each asset separately can be found in section 8.

S1 and S2	Outdays S1	Outdays S2	# Buy Signals (S1 and S2)	# Sell Signals (S1 and S2)	# Days following Buy Signals (S1 and S2)	# Days following Sell Signals (S1)
Average	0	1793	177	176,5	2030	1793

Table 2 - Characterization of Strategies 1 and 2 (Average Results)
Source: The author

S1 and S2	# Profitable Buy Signals (S1 and S2)	# Profitable Sell Signals (S1) / # Unprofitable Sell Signals (S2)	# Unprofitable Buy Signals (S1 and S2)	# Unprofitable Sell Signals(S1) / # Profitable Sell Signals (S2)	Hit Ratio Buy (S1 and S2)	Hit Ratio Sell (S1)
Average	78,9	66,9	98,1	109,7	44,2%	37,7%

Table 3 - Characterization of Strategies 1 and 2 (Average Results) (Continuation)
Source: The author

Being the PSAR an indicator that always places the investor in the market, there are no outdays from following strategy 1. This means investors change from one position to another instantly at the beginning of each trading day, when a new signal appears. For strategy 2, the number of outdays is different from zero, as this strategy exits the market on sell signals. Moreover remember that buy and sell signals are the same for both strategies, only the way investors react to those signals changes[8].

By comparing the average number of signals, it is clear that the number of buy signals is very close to the number of sell signals. This is not surprising since, by construction, the PSAR delivers always one type of signal followed by the other.

The results show, additionally, that the number of profitable buy signals is bigger than the number of sell signals, which translates into a smaller hit ratio for the latter.

5.1.2. Returns

A key aspect about how a trading strategy behaves is naturally how much return it yields. Although a good return is not enough to guarantee the successfulness of a trading strategy, it is certainly a very important aspect.

The results from applying strategies 1 and 2 to the full set of assets can be found in Table 4.

Returns	S1 Buy	S1 Sell	S2 Buy	BH
Brent	0,006%	0,042%	0,010%	0,023%
EUR/USD	0,011%	-0,011%	0,006%	0,005%
JP Morgan Chase	0,027%	-0,018%	0,020%	0,006%
MSCI Japan ETF	-0,053%	0,038%	-0,046%	-0,010%
Portugal Telecom	-0,035%	-0,083%	-0,043%	-0,060%
S&P500 SPDR ETF	-0,017%	0,043%	-0,025%	0,009%
Eurostoxx 50	-0,074%	0,069%	-0,066%	-0,012%
Toyota	-0,029%	0,058%	-0,045%	0,013%
USD/JPY	0,009%	-0,001%	0,007%	0,004%
Gold	0,034%	0,039%	0,038%	0,036%

Table 4 - Strategies 1 and 2 Returns Vs. BH (Average Daily Returns)
Source: The author

To what concerns strategy 1, only EUR/USD, JP Morgan Chase, Portugal Telecom and USD/JPY show a strictly better return when compared to the BH. As for the remaining assets, the PSAR does not show signs of being profitable for either both types or one type of trading signal and therefore these assets are disregarded.

[8]See section 3.3.1

After an in-deep analysis of the results of Table 4, there are two aspects that raise questions about the capabilities of the PSAR.

The first aspect is that the PSAR should work better for assets that show a well-defined trend rather than assets that have a mixed trend. By proving to be profitable for assets that have a mixed trend through time (for example JP Morgan Chase – see Figure 16), in comparison with assets that have a clear trend (for example Gold – see Figure 23), the PSAR is actually going against its fundamentals: It does not make sense for an indicator who has the purpose of determining market trends to trade better when trends are less well defined and consistent through time. In addition, and even if we overlook the fact that the PSAR is actually trading better in mixed trends, it remains unclear why is the PSAR trading properly for some assets that show this type of mixed trend, but not for others who behave similarly. For instance it is unclear why is the PSAR trading correctly for JP Morgan Chase, but not for MSCI Japan ETF (see Figure 17), since both behaved similarly through time.

The second aspect that raises doubts about the PSAR is the fact that it does not seem to function properly when trading counter-trend. This is at least odd, since an indicator that prizes itself of determining correctly market trends should be able to generate correct signals in any circumstance, especially when there are assets in which the dominating trend is well defined. As an example, for Portugal Telecom who exhibited a very pronounced downtrend throughout the time-series (see Figure 18), sell signals have a good performance but buy signals behave poorly. Conversely for Gold, which trended upwards, buy signals have a good performance but sell signals have a bad performance.

This strange behavior suggests that the PSAR has trouble determining which trend is dominating the market and, consequently, it is providing wrong trading signals to investors. Bearing this in mind it is instrumental to determine if the good results for these 4 assets are due to true predictive ability, or instead are due to luck or other circumstances underlying the time-series.

In respect to strategy 2, it is understandable that the same assets who previously showed signs of profitability in strategy 1 also present good returns, since the buy signals triggered for both strategies are the same[9]. The decrease in returns from strategy 1 to strategy 2 is due to the change in the entry time in the underlying assets, as explained in section 3.3.1. Nonetheless the questions raised earlier about the capabilities of the PSAR still subsist here.

5.1.3. Risk

Together with returns, risk is a crucial aspect in determining the goodness of any trading strategy. A superior trading strategy has to either decrease risk or, if it fails to do so, take on "good" risk that allows additional returns to be generated. Table 5 illustrates how strategies 1 and 2 behave in terms of risk.

Risk	S1 Buy	S1 Sell	S2 Buy	BH
Brent	0,042%	0,051%	0,020%	0,046%
EUR/USD	0,004%	0,004%	0,002%	0,004%
JP Morgan Chase	0,062%	0,084%	0,031%	0,072%
MSCI Japan ETF	0,019%	0,026%	0,018%	0,022%
Portugal Telecom	0,037%	0,051%	0,016%	0,044%
S&P500 SPDR ETF	0,012%	0,023%	0,011%	0,017%
Eurostoxx 50	0,017%	0,032%	0,015%	0,023%
Toyota	0,033%	0,043%	0,032%	0,038%
USD/JPY	0,004%	0,005%	0,003%	0,004%
Gold	0,013%	0,014%	0,006%	0,013%

Table 5 - Strategies 1 and 2 Risk Vs. BH (Average Daily Variance)
Source: The author

To what concerns risk, strategy 1 buy signals have always, for the entire set of assets tested, smaller variance than sell signals. When compared to the BH a similar tendency is also verified, as strategy 1 buy signals have always a smaller variance than the BH.

However for sell signals this is not the case. When comparing the variance of these signals against the variance of the BH, it is clear that sell signals display a consistently larger variance.

[9] Bear in mind that in strategy 2, although there are sell signals, the number of days following this signals is equal to 0 because investors stay out of the market when these emerge. Therefore returns and risk for this type of signal are not presented, simply because they are also equal to 0.

This is an indication that the PSAR may not be effective in reducing the risk from holding short positions.

Regarding strategy 2, the results from Table 5 demonstrate that exiting positions instead of holding them translates into a smaller deviation. The volatility is smaller for every asset in strategy 2 when compared to the BH.

Nonetheless neither returns nor variance alone are helpful in understanding which strategy is better regarding how well risk is being rewarded. To overcome this issue, in Table 6 the R3 is presented. This ratio translates how well investors are being reward per unit of total risk they take. Setting the BH strategy as the benchmark, it is possible to determine if investors are getting or not more value from using strategies 1 and 2.

R3	R3 S1 Buy	R3 S1 Sell	R3 S2 Buy	R3 BH
EUR/USD	3,06	-2,74	3,59	1,19
JP Morgan Chase	0,43	-0,21	0,66	0,09
Portugal Telecom	-0,95	-1,62	-2,65	-1,36
USD/JPY	2,37	-0,21	2,07	0,98

Table 6 - Strategies 1 and 2 R3 Vs. BH
Source: The author

The conclusion withdrawn from Table 6 is that strategies 1 and 2 actually do better than the BH in rewarding the risk investors' bear.

Additionally note that, for strategy 1 sell signals, the R3 is better than the BH for 3 of the 4 assets. This is an indication that the excess risk this strategy assumes for sell signals (when comparing to the BH) is being rewarded with extra returns. This means that the PSAR strategies are capable of incorporating good risk, instead of increasing it meaninglessly.

The R3 for the remaining assets can be found in section 8.

5.1.4. Statistical Validation of results– *T-test*

The results presented up to this point indicate that strategies 1 and 2 are successful for 4 assets out of the 10 tested.

However it is dangerous to say that strategies 1 and 2 outperform the BH without testing the significance of the results obtained, especially in light of the odd behavior returns presented in section 5.1.2. Thus, the *t-test* is instrumental to test the truthfulness of the results presented so far.

The results from the application of the *t-test* are displayed in Table 7 and Table 8. The *t-test* for the remaining assets can be found in section 8.

S1	***T-Test* Buy Signals**	Decision	***T-Test* Sell Signals**	Decision	***T-Test* Buy-Sell Spread**	Decision
EUR/USD	0,383	Don’t Reject	-0,893	Don't Reject	1,125	Don't Reject
JP Morgan Chase	0,290	Don't Reject	-0,292	Don't Reject	0,500	Don't Reject
Portugal Telecom	0,450	Don't Reject	-0,383	Don't Reject	0,720	Don't Reject
USD/JPY	0,279	Don't Reject	-0,268	Don't Reject	0,473	Don't Reject

Table 7 - *T-Test* for Strategy 1
Source: The author

S2	***T-Test* Buy Signals**	Decision
EUR/USD	0,066	Don't Reject
JP Morgan Chase	0,242	Don't Reject
Portugal Telecom	0,364	Don't Reject
USD/JPY	0,180	Don't Reject

Table 8 - *T-Test* for Strategy 2
Source: The author

The outcomes of the *t-test* are striking and indicate that, for the 4 assets that showed signs of profitability, there is a big chance that the good results presented are attributable only to circumstantial issues.

From Table 7 we conclude that the returns from following buy and sell signals are not strong enough to reject the null hypothesis stated in equation (19). Additionally not rejecting the hypothesis of the buy-sell spread being equal to zero indicates that there is not sufficient statistical evidence to claim that the PSAR indicator is successful in distinguishing between buy or sell moments in the market. Hence, the outcomes of the *t-test* corroborate the suspicions we raised earlier regarding returns.

The results from Table 8 are in line with the results from Table 7. By not rejecting the null hypothesis for all the assets tested, the conclusions for strategy 2 buy signals are the same as before: there is not enough evidence to reject the null hypothesis of no excess return.

Nevertheless, given the aforementioned limitations of the t-test, in the next section we apply the WRC to further evaluate results.

5.1.5. Statistical Validation of results – White RC

As pointed out in section 3.5.2, although the *t-test* is an easy method to implement, it has some limitations that can distort the conclusions about a given statistic. To overcome this issue we apply the WRC to the 4 assets that showed signs of profitability. The results for the remaining assets are not presented for two reasons: In the first place because they do not show signs of being profitable and, in second place, because the computer time needed to generate a fair amount of simulations for all of them is very high, ranging between 10 to 12 hours per simulated asset.

Table 9 and Table 10 illustrate the results obtained from the WRC procedure for strategies 1 and strategy 2, respectively.

Asset	P-Value
EUR/USD	0.448
JP Morgan Chase	0.356
Portugal Telecom	0.072
USD/JPY	0.466

Table 9 - Results from applying the WRC to Strategy 1
Source: The author

For strategy 1, the results of the WRC point to a non-rejection of the null hypothesis stated in equation (31), meaning that the excess return from following the PSAR strategy is not greater than zero. This supports the conclusions of the *t-test* presented in the previous section, meaning that the good results presented earlier cannot be attributed to exceptional trading skills.

Asset	P-Value
EUR/USD	0.492
JP Morgan Chase	0.428
Portugal Telecom	0.052
USD/JPY	0.518

Table 10 - Results from applying the WRC to Strategy 2
Source: The author

The results of the WRC for strategy 2 point also to the non-rejection of the null hypothesis stated in equation (31), meaning that the excess return from exiting the positions when the PSAR generates a sell signal is not in any way better than following the BH.

The outcomes of the WRC test presented throughout this section, alongside with the results of the *t-test*, highlight the ineffectiveness of the PSAR both as a trading strategy, as well as stop-loss strategy.

5.2. Strategy 3

The goal of strategy 3 is, as stated previously, to test if the results of the BH can be outperformed by incorporating the ADX to help filter out times when the market is non-trending. Like we did in section 5.1, first we provide a brief explanation of how the strategy operates, followed by the analysis of the number of trading signals and the analysis of risks and returns. Lastly, the breakdown of the statistical validation of results is presented.

5.2.1. Characterization

By incorporating the ADX in strategy 3 the quality of the trading signals should be improved. Thus, as now the signals are in principle more accurate, the hit ratio is expected to increase.

These expectations are confirmed as Table 11 and Table 12 show. Once again results for every asset individually can be found in section 8.

S3	Outdays	# Buy Signals	# Sell Signals	# Days following Buy Signals	# Days following Sell Signals
Average	2442	100	94	719	662

Table 11 - Characterization of Strategy 3 (Average Results)
Source: The author

S3	# Profitable Buy Signals	# Profitable Sell Signals	# Unprofitable Buy Signals	# Unprofitable Sell Signals	Hit Ratio Buy	Hit Ratio Sell
Average	52	42	48	53	53%	44%

Table 12 - Characterization of Strategy 3 (Average Results) (Continuation)
Source: The author

The number of days following buy and sell signals is diminished due to the fact that, with this ADX setting, a signal is more difficult to generate when compared to strategies 1 and 2. On the other hand, the number of outdays increased as it should, since by following this strategy investors are placed out of the market a greater amount of times.

However it is important to note that the increase in the hit ratio for strategy 3 does not mean that returns are superior to the ones presented earlier. It simply means that the now the chances of picking a profitable trade increase. The increase in the hit ratio does not guarantee that the profitable returns outweigh unprofitable returns.

5.2.2. Returns

The returns from Strategy 3 are surprising, as they behave contrary to what would be expected.

By using the ADX to filter out times when the market is non-trending, one would expect to see an increase in returns for all, or at least some of the assets.

However, by using this setting, there are only two assets that prove to be strictly better than the BH: Portugal Telecom and Eurostoxx 50.

Returns	S3 Buy	S3 Sell	BH
Brent	-0,144%	-0,125%	0,023%
EUR/USD	-0,011%	-0,011%	0,005%
JP Morgan Chase	0,071%	0,069%	0,006%
MSCI Japan ETF	-0,078%	0,111%	-0,010%
Portugal Telecom	0,020%	-0,052%	-0,060%
S&P500 SPDR ETF	-0,032%	0,021%	0,009%
Eurostoxx 50	0,181%	-0,184%	-0,012%
Toyota	0,008%	0,067%	0,013%
USD/JPY	0,011%	0,004%	0,004%
Gold	0,002%	0,068%	0,036%

Table 13 - Strategy 3 Returns Vs. BH (Average Daily Returns)
Source: The author

This is unexpected not only because the ADX fails to improve the results from previous strategies, but also because it worsens them. The majority of the assets that were strictly profitable in previous strategies are now included in the group of unprofitable assets.

Nonetheless, in light of the results presented previously in sections 5.1.2 and 5.1.4, this is understandable.

By filtering out times where the market is moving at a slower pace, the ADX indicator is actually magnifying the bad decisions of the PSAR. If investors enter a trade when the market is trending, thus moving faster, the chances are that good or bad decisions will have a considerably bigger impact than they would have if they entered a trade when markets are quieter. If investors follow a wrong signal given by the PSAR when the ADX is providing a reading above 25, then they stand to lose more simply because the market is moving faster against their position.

The fact that the PSAR is unable to distinguish properly between when to buy and when to sell (as seen from the *t-test* in section 5.1.4), is thus the main reason driving the ineffectiveness of the ADX.

Still, the good results for both Portugal Telecom and Eurostoxx 50 cannot go unnoticed. While it is not believable that the good results for these two assets are due to anything else other than circumstances underlying the time-series[10], without validating them using the same statistical tools as before, it is not possible to state clearly that strategy 3 does not work.

5.2.3. Risk

Concerning risk, we observe that including the ADX does not guarantee an overall reduction in the variance of returns. Although for buy signals the variance is sometimes reduced when compared to the BH, the variance for sell signals is always increased, as Table 14 suggests. This is in line with the results presented previously in section 5.1.3.

Risk	Buy	Sell	BH
Brent	0,048%	0,063%	0,046%
EUR/USD	0,004%	0,005%	0,004%
JP Morgan Chase	0,055%	0,100%	0,072%
MSCI Japan ETF	0,028%	0,042%	0,022%
Portugal Telecom	0,038%	0,060%	0,044%
S&P500 SPDR ETF	0,016%	0,038%	0,017%
Eurostoxx 50	0,024%	0,044%	0,023%
Toyota	0,042%	0,061%	0,038%
USD/JPY	0,004%	0,006%	0,004%
Gold	0,015%	0,018%	0,013%

Table 14 - Strategy 3 Risk Vs. BH (Average Daily Variance)
Source: The author

[10] Given the limitations the PSAR showed throughout section 5.1.

Nevertheless risk seems to be well rewarded, since both profitable assets register a better R3 when compared to the BH, as Table 15 shows. This is, once again, positive for sell signals, as it proves that the increased risk is also compensated with increased returns. The R3 for the remaining assets can be found in section 8.

S3	R3 Buy	R3 Sell	BH
Portugal Telecom	0,53	-0,87	-1,36
Eurostoxx 50	7,38	-4,17	-0,50

Table 15 - Strategy 3 R3 Vs. BH
Source: The author

5.2.4. Statistical Validation of results – *T-test*

Up to this point, 2 of the 10 assets tested show signs of being profitable when the ADX is applied jointly with the PSAR. Nevertheless, the *t-test* is needed once again to access statistical validity of results obtained so far.

Table 16 illustrates the outcomes of the test:

S3	*T-Test* Buy Signals	Decision	*T-Test* Sell Signals	Decision	*T-Test* Buy-Sell Spread	Decision
Portugal Telecom	1,069	Don't Reject	0,085	Don't Reject	0,667	Don't Reject
Eurostoxx 50	2,928	Reject	-1,917	Don't Reject	3,500	Reject

Table 16 - *T-Test* for Strategy 3
Source: The author

As expected, the conclusions withdrawn from the *t-test* for strategy 3 are similar to the conclusions withdrawn for strategies 1 and 2.

Like Table 16 shows, for Portugal Telecom, there is not enough evidence to claim that the returns from following buy and sell signals are different from zero. Moreover, the spread between buy and sell signals indicates that the strategy is not able to distinguish moments when to go long on the asset from moments when to go short. This implies that both null hypotheses in section 3.5.1 are not rejected, thus pointing to the non-existence of any trading ability.

For Eurostoxx50 the conclusion is different. The *t-test* points to a rejection of the null hypothesis for buy signals and buy-sell spread, meaning that there is a chance the strategy is truly profitable.

Concerning sell signals, although the decision is the non-rejection of the null hypothesis (meaning that, unlike buy signals, there appears to be no signs off true predictive ability), the test statistic is very near the critical value of -1.96. This suggests that selecting for example a 90% degree of confidence, would make this results statistically significant. Therefore, although the test clearly does not reject the null hypothesis of equality with zero, it does so by a very narrow margin. Keeping that in mind, for the sake of the argument we consider the asset valid in terms of the *t-test* and proceed to the analysis of the WRC. The WRC is vital in this context because Eurostoxx 50 is the first asset showing some signs of true profitability. Nevertheless, once again, it is not believable that these good results are something other than pure coincidence.

5.2.5. Statistical Validation of results – White RC

The results presented so far for Portugal Telecom and Eurostoxx50 point in the distinct directions. While for Portugal Telecom strategy 3 does not seem to be profitable, for Eurostoxx 50 the outcomes of the *t-test* suggest otherwise. In this context, and bearing in mind that sell signals for Eurostoxx 50 show signs of being at least to some extent statistically irrelevant, it is essential to conduct the validation of the *t-test* with the WRC, in order to clear any remaining doubts.

Table 17 illustrates the outcomes of the WRC test for Portugal Telecom and Eurostoxx 50. The WRC for the remaining assets is not presented for the same reasons stated in section 5.1.5.

Asset	P-Value
Portugal Telecom	0.078
Eurostoxx 50	0.512

Table 17 - Results from applying the WRC to Strategy 3
Source: The author

The application of the WRC procedure to the results of strategy 3, for Portugal Telecom and Eurostoxx50, allows withdrawing conclusions similar to the ones presented earlier for strategies 1 and 2. The non-rejection of the null hypothesis is a strong evidence supporting the non-existence of superior predictive ability, when random observations of excess returns are generated. Hence the WRC shows that using the ADX jointly with the PSAR does not yield better results than the BH, for both assets. This confirms that apparent good trading skills cannot be attributed directly to strategy 3 itself and thus the good results obtained for Eurostoxx 50 are statistically invalid.

6. Discussion and conclusions

The goal of this dissertation was to investigate the effectiveness of the PSAR indicator both as a trading strategy, as well as a stop-loss strategy, and to improve its profitability by including the ADX as a mean of filtering incorrect trading signals.

Even though there is, for each of the 3 trading strategies tested, some evidence indicating that the strategies may indeed deliver increased returns and reduced risks, the truth is that there are no statistical grounds to claim they are truly profitable.

Thus, since we cannot guarantee with certainty that the results obtained are actually due to superior predictive ability, the outcome is the rejection of the 3 hypothesis posed in section 3.1. In other words, the PSAR is not effective as a trading strategy, it is not effective as a stop-loss strategy and it is not effective when used in conjunction with the ADX. Our conclusions are not only sustained by the outcomes of the *t-test* and the WRC procedure, they are also enforced by the abnormal behavior the returns of PSAR displayed in strategies 1 and 2.

In light of the presented results it is clear that the primary pitfall of the PSAR is that fact that it simply cannot distinguish between buy moments and sell moments in the market.

In the context of this dissertation this is a great limitation, since all the strategies and indicators rely on the effectiveness of the signals generated by the PSAR.

Our findings are thus in line with the conclusions of Metghalchi *et al*.(2014), who find evidence of profitability but not of statistical significance.

Comparing our results with the results of Yazdi and Lashkari (2010), we can see certain points of contact, despite the fact the conclusions we draw are somewhat different. Yazdi and Lakashari find evidence of profitability for the same two exchange-rates that also showed signs of being profitable in our analysis, but do not mention if their results have statistical validation. However they argue that buy signals are more profitable than sell signals, when our findings show otherwise.

From an EMH perspective, it is safe to say that the outcome of our work supports the idea that one cannot outperform an efficient market. Nonetheless this dissertation does not provide any closure to this discussion. In fact this dispute will never be fully resolved.

While advocates of the EMH would say that our study shows that one cannot truly profit from using past data to make predictions about the future, advocates of TA will have a different argument. They will argue that applying the PSAR mechanically would never yield good results because it cannot capture on its own complex patterns that an experienced technical analyst would perceive.

Having said that, the choice about whether the EMH should be disregard in place of TA depends ultimately on the investor, since there is more than enough evidence to supports both views.

There is still an aspect about our dissertation that unfortunately remained unclear: the usefulness of the ADX.

Despite the fact strategy 3 relied on the ADX and yet delivered bad results, we cannot blame the ADX entirely, as the main reason pushing forward the bad results is the ineffectiveness of the PSAR.

Besides notice that when the ADX is applied together with the PSAR, a significant number of assets go from being profitable to unprofitable. From the perspective of the ADX this is actually positive, as it indicates that the ADX determines correctly when the market is moving faster, otherwise we would not see an increase in the number of assets with negative returns.

Thus, an interesting starting point for further investigation would be to test the usefulness of the ADX indicator, either as a primary trading strategy or as an auxiliary indicator to another technical indicator.

Concerning the PSAR one curious research would be to change the original settings of the indicator, which we used in this dissertation, to another different setting. This would allow understanding definitively if the PSAR is a valuable trading mechanism or if, on the other hand, it is old fashioned and outdated.

Although the outcomes of our dissertation do not favor the PSAR, there is one limitation that is harmful to the profitability of the indicator and that would not exits if it was used in the context of real life trading. This limitation is the fact that we use the PSAR and the ADX lagged by one day.

This is a limitation because in real trading, investors can monitor the market and anticipate which position they should hold for the next day, even if the market is not yet closed. As such, our model cannot replace the critical judgment of an investor, and therefore acts slower and loses some of its potential. To overcome this issue one would have to use a PSAR setting based on intraday data that unfortunately was not available. However this is a limitation that affects every theoretical trading model that relies on past data, either it is the PSAR or any other technical indicator.

7. References

Alexander, S. S. 1961. Price movements in speculative markets: Trends or random walks. ***Industrial Management Review***, 2: 7–26.

Aronson, D. 2007. ***Evidenced Based Technical Analysis***. New Jersey.

Barber, B. M., & Odean, T. 2001. Boys will be boys: Gender, overconfidence and common stock investment. ***The Quarterly Journal of Economics***, 116(1): 261–292.

Bessembinder, H., & Chan, K. 1997. Market efficiency and the returns to technical analysis. ***Financial Management***, 27(2): 5–17.

Black, F. 1986. Noise. ***The Journal of Finance***, 41(3): 529–544.

Brock, W., Lakonishok, J., & Lebaron, B. 1992. Simple technical trading rules and the stochastic properties of stock returns. ***The Journal of Finance***, 47(5): 1731–1764.

Caginalp, G., & Laurent, H. 1998. The predictive power of price patterns. ***Applied Mathematical Finance***, 5: 181–205.

Chong, & Ng, W.-K. 2008. Technical analysis and the London stock exchange : Testing the MACD and RSI rules using the FT30. ***Applied Economics Letters***, 15: 1111–1114.

Chong, T. T.-L., Li, E. H.-T., & Kong, K. T.-K. 2011. Are trading rules profitable in exchange-traded funds? ***Technology and Investment***, 2: 129–133.

Cootner, P. H. 1962. Stock Prices: Random vs. systematic changes. ***Industrial Management Review***, 3: 25–45.

Cowles, A., & Jones, H. E. 1937. Some a posteriori probabilities in stock market action. ***Econometrica***, 5(3): 280–294.

Curcio, R., & Goodhart, C. 1992. ***When support/resistance levels are broken, can profits be made? Evidence from the foreign exchange market***. No. 142. London.

Diebold, F., & Mariano, R. 1995. Diebold, Mariano (1995) Comparing predictive Accuracy.pdf. ***Econometrica***, 13: 253–256.

Dorfleitner, G., Klein, C., & Kundisch, D. 2007. ***Technical analysis as a method of risk management***. Augsburg.

Efron, B. 1982. ***The jackknife, the bootstrap, and other resampling plans***. Vermont: Capital City Press.

Elder, A. 2002. ***Come into my trading room. A complete guide to trading***. New York: John Wiley & Sons, Inc.

Elder, A. 2008. ***Sell and Sell Short***. New York: John Wiley & Sons, Inc.

Fama, E. 1965a. The behavior of stock-market prices. ***The Journal of Business***, 38(1): 34–105.

Fama, E. 1965b. Random walks in stock market prices. ***Financial Analysts Journal***, 21(5): 55–59.

Fama, E., & Blume, M. E. 1966. Filter rules and stock-market trading. ***The Journal of Business***, 39(1): 226–241.

Flanegin, F. R., & Rudd, D. P. 2005. Should investment professors join the "crowd." ***Managerial Finance***, 31(5): 28–37.

Gervais, S., & Odean, T. 2001. Learning to be overconfident. ***The Review of Financial Studies***, 14(1): 1–27.

Gomes da Silva, M. 2013. ***Bolsa: Investir nos mercados financeiros***. Olival Basto: Bookout.

Horton, M. J. 2009. Stars, crows, and doji: The use of candlesticks in stock selection. ***The Quarterly Review of Economics and Finance***, 49(2): 283–294.

Kahneman, D., & Tversky, A. 1974. Judgment under uncertainty: Heuristics and biases. ***Science***, 185(4157): 1124–1131.

Kahneman, D., & Tversky, A. 1979. Prospect theory: An analysis of decision under risk. ***Econometrica***, 47(2): 269–292.

Kaminski, K. M., & Lo, A. W. 2014. When do stop-loss rules stop losses? ***Journal of Financial Markets***, 18: 234–254.

Kase, C. A. 1996. ***Trading with the odds***. New York: McGraw-Hill.

Kirkpatrick, C. D., & Dahlquist, J. R. 2007. ***Technical Analysis - The Complete Resource for Financial Market Technicians***. New Jersey: FT Press.

Kunsch, H. 1989. The Jackknife and the Bootstrap for General Stationary Observations. ***The Annals of Statistics***, 17: 1217–1241.

Lai, H.-W., Chen, C.-W., & Huang, C.-S. 2010. Technical analysis, investment psychology, and liquidity provision: Evidence from the Taiwan stock market. ***Emerging Markets Finance & Trade***, 46(5): 18–38.

Libertini, N. J. 2013. The impact of stop losses on short-term countertrend trading strategies. ***Journal of Investment Strategies***, 2(4): 59–81.

Lim, S., Hisarli, T., & Shi He, N. 2014. The profitability of a combined signal approach : Bollinger bands and the ADX. ***International Federation of Technical Analysts***, 1: 30–36.

Lo, A. W., & MacKinlay, C. A. 1988. Stock market prices do not follow random walks: Evidence from a simple specification test. ***The Review of Financial Studies***, 1(1): 41–66.

Lu, T.-H., & Chen, J. 2013. Candlestick charting in european markets. ***The Finsia Journal of Applied Finance***, 1(2): 20–25.

Mandelbrott, B. 1963. The variation of certain speculative prices. ***The Journal of Business***, 36(4): 394–419.

Menkhoff, L., & Taylor, M. 2007. The obstinate passion of foreign exchange professionals: Technical analysis. ***Journal of Economic Literature***, 45: 936–972.

Metghalchi, M., Kagochi, J., & Hayes, L. A. 2014. Contrarian technical trading rules: Evidence from Nairobi stock index. ***The Journal of Applied Business Research***, 30(3): 833–846.

Metghalchi, M., Marcucci, J., & Chang, Y.-H. 2012. Are moving average trading rules profitable? Evidence from the European stock markets. ***Applied Economics***, 44(12): 1539–1559.

Murphy, J. J. 1999. ***Technical analysis of the financial markets: A comprehensive guide to trading methods and applications***. New York: New York Institute of Finance.

O'Neil, W. J. 1988. ***How to make money in stocks***. New York: McGraw-Hill.

Odean, T. 1998a. Are investors reluctant to realize their losses ? ***The Journal of Finance***, 53(5): 1775–1798.

Odean, T. 1998b. Volume, volatility, price and profit - When all traders are above average. ***The Journal of Finance***, 53(6): 1887–1933.

Osler, C. 2000. Support for resistance: Technical analysis and intraday exchange rates. ***Federal Reserve Bank of New York Economic Policy Review***, 6(2): 53–68.

Park, C.-H., & Irwin, S. H. 2004. ***The profitability of technical analysis: A review***. Urbana: University of Illinois at Urbana-Champaign.

Politis, D., & Romano, R. 1994. The Stationary Bootstrap. ***Journal of the American Statistical Association***, 89(428): 1303–1313.

Ready, M. J. 2002. Profits from technical trading rules. ***Financial Management***, 31(3): 43–61.

Sornette, D. 2003. Critical market crashes. ***Physics Reports***, 378(1): 1–98.

Sullivan, R., Timmermann, A., & White, H. 1999. Data-Snooping , Technical Trading Rule Performance, and the Bootstrap. ***The Journal of Finance***, 54(5): 1647–1691.

Tatro, Q. 2011. ***Trade the trader***. New Jersey: FT Press.

Taylor, M. P., & Allen, H. 1992. The use of technical analysis in the foreign exchange market. ***Journal of International Money and Finance***, 11(3): 304–314.

Tharp, V. K. 1999. ***Trade your way to financial freedom***. New York: McGraw-Hill.

Tooth, S. M. 2014. On the efficacy of stop-loss trategies. ***The Journal of Trading***, 9(4): 100–107.

Vidotto, R. S., & Zambon, A. C. 2009. O moving average convergence-divergence como ferramenta para a decisão de investimentos no mercado de ações. ***Revista de Administração Contemporânea***, 13(2): 291–309.

Vince, R. 1990. ***Portfolio management formulas***. New York: John Wiley & Sons, Inc.

West, K. 1996. Asymptotic Inference About Predictive Ability. ***Econometrica***, 64: 1067–1084.

White, H. 2000. A Reality Chech For Data Snooping. ***Econometrica***, 68(5): 1097–1126.

Wilder, W. 1978. ***New concepts in technical trading systems***. North Carolina: Hunter Publishing Company.

Yazdi, S. H. M., & Lashkari, Z. H. 2010. ***Technical analysis of forex by parabolic SAR indicator***. Malaysia.

8. Appendix

8.1. Example of the PSAR calculation and application 63

8.2. Appendix A-Brent 64

8.2.1. Characterization 64

8.2.2. Risk and Returns 65

8.2.3. Statistical Validation: *T-test* 65

8.3. Appendix B-EUR/USD 66

8.3.1. Characterization 66

8.3.2. Risk and Returns 67

8.3.3. Statistical Validation: *T-test* 67

8.4. Appendix C-JP Morgan Chase 68

8.4.1. Characterization 68

8.4.2. Risk and Return 69

8.4.3. Statistical Validation: *T-test* 69

8.5. Appendix D-MSCI Japan ETF 70

8.5.1. Characterization 70

8.5.2. Risk and Returns 71

8.5.3. Statistical Validation: *T-test* 71

8.6. Appendix E-Portugal Telecom 72

8.6.1. Characterization 72

8.6.2. Risk and Returns 73

8.6.3. Statistical Validation: *T-test* 73

8.7. Appendix F-S&P500 SPDR ETF 74

8.7.1. Characterization 74

8.7.2. Risk and Returns 75

8.7.3. Statistical Validation: *T-test* 75

8.8. Appendix G-Eurostoxx 50 76

8.8.1. Characterization 76

8.8.2. Risk and Returns 77

8.8.3. Statistical Validation: *T-test* 77

8.9. Appendix H-Toyota 78

8.9.1. Characterization 78

8.9.2. Risk and Returns 79

8.9.3. Statistical Validation: *T-test* 79

8.10. Appendix I-USD/JPY 80

8.10.1. Characterization 80

8.10.2. Risk and Returns 81

8.10.3. Statistical Validation: *T-test* 81

8.11. Appendix J-Gold 82

8.11.1. Characterization 82

8.11.2. Risk and Returns 83

8.11.3. Statistical Validation: *T-test* 83

8.1. Example of the PSAR calculation and application

SAR Uptrend

		High	Low	SAR	EP	EP-SAR	AF	AF(EP-SAR)
	17-Mar-10	47.85	47.48					
	18-Mar-10	47.83	47.55					
	19-Mar-10	47.95	47.32					
	22-Mar-10	48.11	47.25					
1	23-Mar-10	48.30	47.77	47.25	48.30	1.05	0.02	0.02
2	24-Mar-10	48.17	47.91	47.25	48.30	1.05	0.02	0.02
3	25-Mar-10	48.60	47.90	47.27	48.60	1.33	0.04	0.05
4	26-Mar-10	48.33	47.74	47.32	48.60	1.28	0.04	0.05
5	29-Mar-10	48.40	48.10	47.38	48.60	1.22	0.04	0.05
6	30-Mar-10	48.55	48.06	47.42	48.60	1.18	0.04	0.05
7	31-Mar-10	48.45	48.07	47.47	48.60	1.13	0.04	0.05
8	1-Apr-10	48.70	47.79	47.52	48.70	1.18	0.06	0.07
9	5-Apr-10	48.72	48.14	47.59	48.72	1.13	0.08	0.09
10	6-Apr-10	48.90	48.39	47.68	48.90	1.22	0.10	0.12
11	7-Apr-10	48.87	48.37	47.80	48.90	1.10	0.10	0.11
12	8-Apr-10	48.82	48.24	47.91	48.90	0.99	0.10	0.10
13	9-Apr-10	49.05	48.64	48.01	49.05	1.04	0.12	0.12
14	12-Apr-10	49.20	48.94	48.13	49.20	1.07	0.14	0.15
15	13-Apr-10	49.35	48.86	48.28	49.35	1.07	0.16	0.17

Blue areas are given values
Yellow area shows example.

Figure 12 - Uptrend PSAR calculation and illustration
Source: www.stockcharts.com consulted on 19/7/15

SAR Downtrend

		High	Low	SAR	EP	SAR-EP	AF	AF(SAR-EP)
	13-Jan-10	46.44	45.56					
	14-Jan-10	46.47	46.17					
	15-Jan-10	46.50	45.60					
	19-Jan-10	46.59	45.90					
1	20-Jan-10	46.55	45.38	46.59	45.38	1.21	0.02	0.024
2	21-Jan-10	46.30	45.25	46.59	45.25	1.34	0.04	0.054
3	22-Jan-10	45.43	43.99	46.55	43.99	2.56	0.06	0.154
4	25-Jan-10	44.55	44.07	46.40	43.99	2.41	0.06	0.144
5	26-Jan-10	44.84	44.00	46.26	43.99	2.26	0.06	0.136
6	27-Jan-10	44.80	43.96	46.12	43.96	2.16	0.08	0.173
7	28-Jan-10	44.38	43.27	45.95	43.27	2.67	0.10	0.267
8	29-Jan-10	43.97	42.58	45.68	42.58	3.10	0.12	0.371
9	1-Feb-10	43.23	42.83	45.31	42.58	2.72	0.12	0.327
10	2-Feb-10	43.73	42.98	44.98	42.58	2.40	0.12	0.288
11	3-Feb-10	43.92	43.37	44.69	42.58	2.11	0.12	0.253
12	4-Feb-10	43.61	42.57	44.44	42.57	1.87	0.14	0.261
13	5-Feb-10	42.97	42.07	44.18	42.07	2.10	0.16	0.337
14	8-Feb-10	43.13	42.59	43.84	42.07	1.77	0.16	0.283
15	9-Feb-10	43.46	42.71	43.56	42.07	1.49	0.16	0.238

Blue areas are given values
Yellow area shows example.

Figure 13 - Downtrend PSAR calculation and illustration
Source: www.stockcharts.com consulted on 19/7/15

8.2. Appendix A-Brent

8.2.1. Characterization

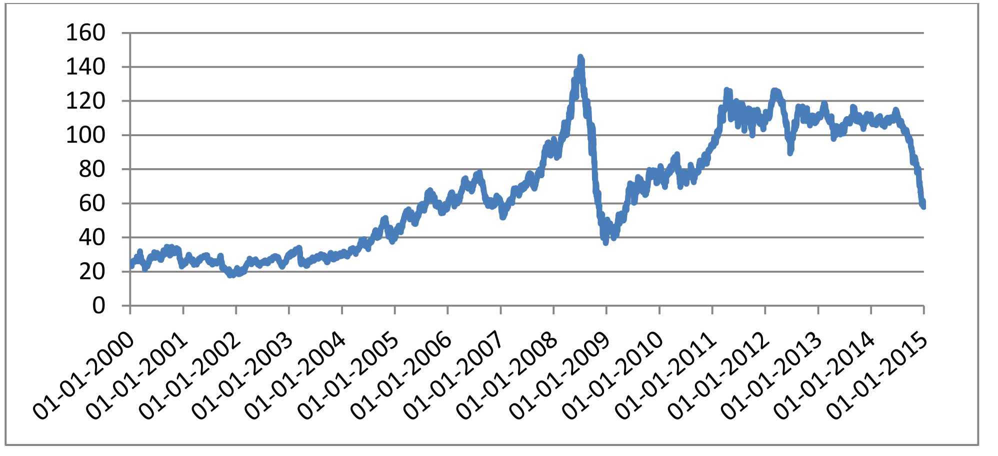

Figure 14 - Evolution of Brent asset prices
Source: The author

	Outdays	# Buy Signals	# Sell Signals	# Days following Buy signals	# Days following Sell signals
S1	0	189	188	2034	1798
S2	1798	189	188	2034	0
S3	2316	115	116	739	777

Table 18 - Strategies Characterization
Source: The author

	# Profitable Buy Signals	# Profitable Sell Signals (S1 & S3)/ # Unprofitable Sell Signals (S2)	# Unprofitable Buy Signals	# Unprofitable Sell Signals (S1 & S3)/ # Profitable Sell Signals (S2)	Hit Ratio Buy	Hit Ratio Sell
S1	79	57	110	131	41,8%	30,3%
S2	79	131	110	57	41,8%	NA
S3	46	47	70	69	39,7%	40,5%

Table 19 - Strategies Characterization (Continuation)
Source: The author

8.2.2. Risk and Returns

Average Daily Returns	Buy	Sell	Average Daily Variance	Buy	Sell	R3	Buy	Sell
BH	0,023%	NA	BH	0,046%	NA	BH	0,50	NA
S1	0,006%	0,042%	S1	0,042%	0,051%	S1	0,15	0,83
S2	0,010%	NA	S2	0,020%	NA	S2	0,50	NA
S3	-0,144%	-0,125%	S3	0,048%	0,063%	S3	-3,03	-1,98

Table 20 - Risk and Returns analysis for Brent
Source: The author

8.2.3. Statistical Validation: *T-test*

	T-Test **Buy Signals**	**Decision**	***T-Test*** **Sell Signals**	**Decision**	***T-Test*** **Buy-Sell Spread**	**Decision**
S1	-0,298	Don't Reject	0,302	Don't Reject	-0,518	Don't Reject
S2	-0,282	Don't Reject	NA	NA	NA	NA
S3	-1,916	Don't Reject	-1,536	Don't Reject	-0,160	Don't Reject

Table 21 - ***T-Test*** **for Brent**
Source: The author

NA: As investors do not trade the sell signals of S2 (they only exit positions) it is not possible to compute the measurements that rely on the daily return and variance of these signals.

8.3. Appendix B-EUR/USD

8.3.1. Characterization

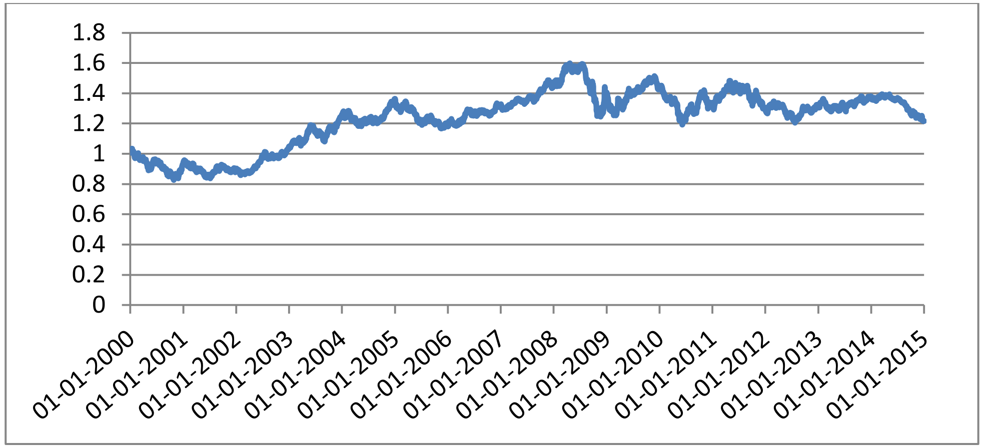

Figure 15 - Evolution of EUR/USD asset prices
Source: The author

	Outdays	# Buy Signals	# Sell Signals	# Days following Buy signals	# Days following Sell signals
S1	0	195	194	2051	1862
S2	1862	195	194	2051	0
S3	2309	116	111	807	797

Table 22 - Strategies Characterization
Source: The author

	# Profitable Buy Signals	# Profitable Sell Signals (S1 & S3)/ # Unprofitable Sell Signals (S2)	# Unprofitable Buy Signals	# Unprofitable Sell Signals (S1 & S3)/ # Profitable Sell Signals (S2)	Hit Ratio Buy	Hit Ratio Sell
S1	139	131	56	63	71,3%	67,5%
S2	139	63	56	131	71,3%	NA
S3	76	71	40	40	65,5%	64,0%

Table 23 - Strategies Characterization (Continuation)
Source: The author

8.3.2. Risk and Returns

Average Daily Returns	Buy	Sell	Average Daily Variance	Buy	Sell	R3	Buy	Sell
BH	0,005%	NA	BH	0,004%	NA	BH	1,19	NA
S1	0,0112%	-0,0113%	S1	0,004%	0,004%	S1	3,06	-2,74
S2	0,006%	NA	S2	0,002%	NA	S2	3,59	NA
S3	-0,0106%	-0,0115%	S3	0,004%	0,005%	S3	-2,72	-2,49

Table 24 - Risk and Returns analysis for EUR/USD
Source : The author

8.3.3. Statistical Validation: *T-test*

	T-Test **Buy Signals**	**Decision**	***T-Test*** **Sell Signals**	**Decision**	***T-Test*** **Buy-Sell Spread**	**Decision**
S1	0,383	Don't Reject	-0,893	Don't Reject	1,125	Don't Reject
S2	0,066	Don't Reject	NA	NA	NA	NA
S3	-0,635	Don't Reject	-0,622	Don't Reject	0,026	Don't Reject

Table 25 - *T-Test* for EUR/USD
Source: The author

NA: As investors do not trade the sell signals of S2 (they only exit positions) it is not possible to compute the measurements that rely on the daily return and variance of these signals.

8.4. Appendix C-JP Morgan Chase

8.4.1. Characterization

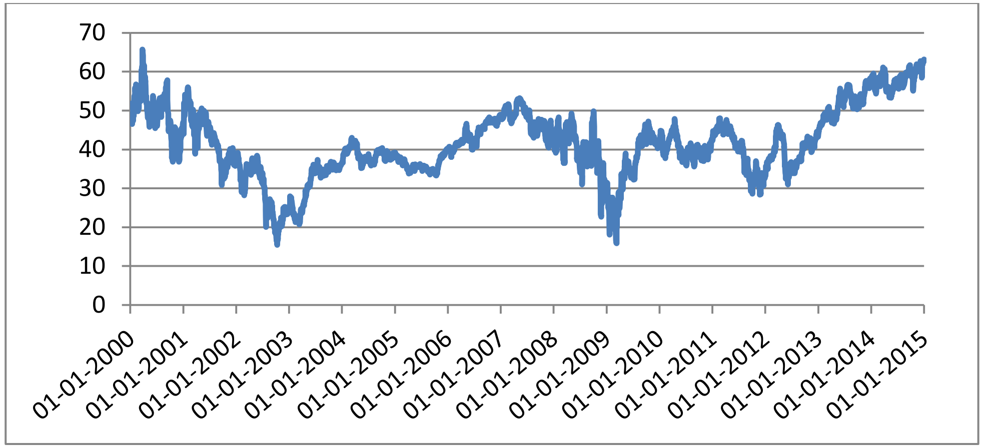

Figure 16 - Evolution of JP Morgan Chase asset prices
Source: The author

	Outdays	# Buy Signals	# Sell Signals	# Days following Buy signals	# Days following Sell signals
S1	0	176	175	2045	1728
S2	1728	176	175	2045	0
S3	2516	97	90	651	606

Table 26 - Strategies Characterization
Source: The author

	# Profitable Buy Signals	# Profitable Sell Signals (S1 & S3)/ # Unprofitable Sell Signals (S2)	# Unprofitable Buy Signals	# Unprofitable Sell Signals (S1 & S3)/ # Profitable Sell Signals (S2)	Hit Ratio Buy	Hit Ratio Sell
S1	74	60	102	115	42,0%	34,3%
S2	74	115	102	60	42,0%	NA
S3	44	37	53	53	45,4%	41,1%

Table 27 - Strategies Characterization (Continuation)
Source: The author

8.4.2. Risk and Return

Average Daily Returns	Buy	Sell
BH	0,006%	NA
S1	0,027%	-0,018%
S2	0,020%	NA
S3	0,071%	0,069%

Average Daily Variance	Buy	Sell
BH	0,072%	NA
S1	0,062%	0,084%
S2	0,031%	NA
S3	0,055%	0,100%

R3	Buy	Sell
BH	0,09	NA
S1	0,43	-0,21
S2	0,66	NA
S3	1,28	0,69

Table 28 - Risk and Returns analysis for JP Morgan Chase
Source: The author

8.4.3. Statistical Validation: *T-test*

	T-Test Buy Signals	Decision	*T-Test* Sell Signals	Decision	*T-Test* Buy-Sell Spread	Decision
S1	0,290	Don't Reject	-0,292	Don't Reject	0,500	Don't Reject
S2	0,242	Don't Reject	NA	NA	NA	NA
S3	0,632	Don't Reject	0,461	Don't Reject	0,013	Don't Reject

Table 29 - *T-Test* for JP Morgan Chase
Source: The author

NA: As investors do not trade the sell signals of S2 (they only exit positions) it is not possible to compute the measurements that rely on the daily return and variance of these signals.

8.5. Appendix D-MSCI Japan ETF

8.5.1. Characterization

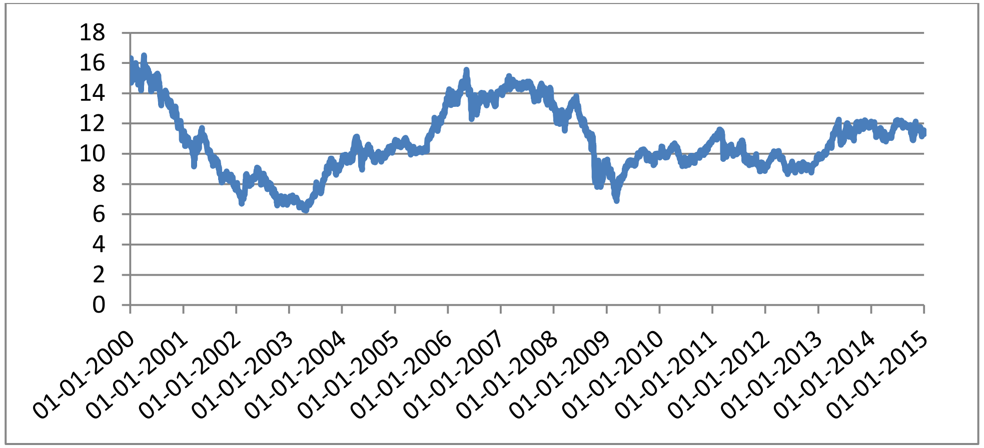

Figure 17 - Evolution of MSCI Japan ETF asset prices
Source: The author

	Outdays	# Buy Signals	# Sell Signals	# Days following Buy signals	# Days following Sell signals
S1	0	150	149	1998	1775
S2	1775	150	149	1998	0
S3	2795	64	64	528	450

Table 30 - Strategies Characterization
Source: The author

	# Profitable Buy Signals	# Profitable Sell Signals (S1 & S3)/ # Unprofitable Sell Signals (S2)	# Unprofitable Buy Signals	# Unprofitable Sell Signals (S1 & S3)/ # Profitable Sell Signals (S2)	Hit Ratio Buy	Hit Ratio Sell
S1	62	46	88	103	41,3%	30,9%
S2	62	103	88	46	41,3%	NA
S3	46	26	18	38	71,9%	40,6%

Table 31 - Strategies Characterization (Continuation)
Source: The author

8.5.2. Risk and Returns

Average Daily Returns	Buy	Sell	Average Daily Variance	Buy	Sell	R3	Buy	Sell
BH	-0,010%	NA	BH	0,022%	NA	BH	-0,45	NA
S1	-0,053%	0,038%	S1	0,019%	0,026%	S1	-2,71	1,47
S2	-0,046%	NA	S2	0,018%	NA	S2	-2,63	NA
S3	-0,078%	0,111%	S3	0,028%	0,042%	S3	-2,74	2,65

Table 32 - Risk and Returns analysis for MSCI Japan ETF
Source: The author

8.5.3. Statistical Validation: *T-test*

	T-Test **Buy Signals**	Decision	***T-Test*** **Sell Signals**	Decision	***T-Test*** **Buy-Sell Spread**	Decision
S1	-1,075	Don't Reject	1,058	Don't Reject	-1,837	Don't Reject
S2	-0,943	Don't Reject	NA	NA	NA	NA
S3	-0,876	Don't Reject	1,215	Don't Reject	-1,556	Don't Reject

Table 33 - *T-Test* for MSCI Japan ETF
Source: The author

NA: As investors do not trade the sell signals of S2 (they only exit positions) it is not possible to compute the measurements that rely on the daily return and variance of these signals.

8.6. Appendix E-Portugal Telecom

8.6.1. Characterization

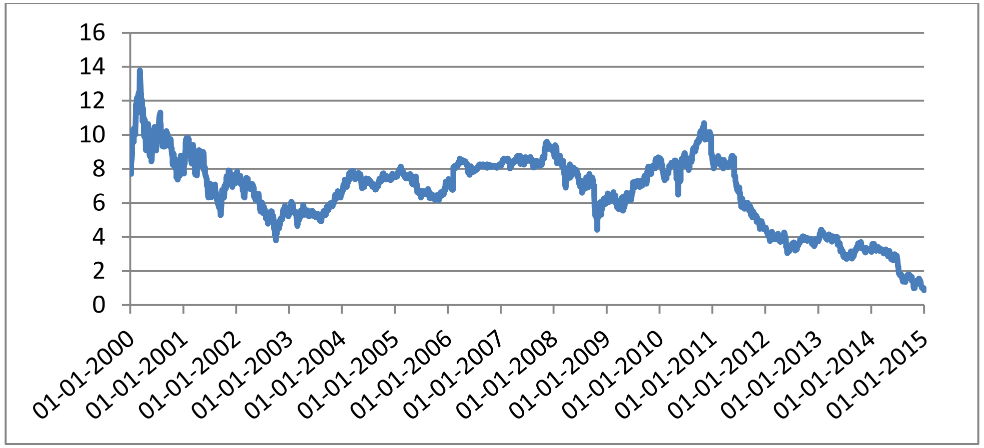

Figure 18 - Evolution of Portugal Telecom asset prices
Source: The author

	Outdays	# Buy Signals	# Sell Signals	# Days following Buy signals	# Days following Sell signals
S1	0	151	152	1834	1980
S2	1980	151	152	1834	0
S3	2142	97	107	854	818

Table 34 - Strategies Characterization
Source: The author

	# Profitable Buy Signals	# Profitable Sell Signals (S1 & S3)/ # Unprofitable Sell Signals (S2)	# Unprofitable Buy Signals	# Unprofitable Sell Signals (S1 & S3)/ # Profitable Sell Signals (S2)	Hit Ratio Buy	Hit Ratio Sell
S1	57	56	94	96	37,7%	36,8%
S2	57	96	94	56	37,7%	NA
S3	43	45	54	62	44,3%	42,1%

Table 35 - Strategies Characterization (Continuation)
Source: The author

8.6.2. Risk and Returns

Average Daily Returns	Buy	Sell	Average Daily Variance	Buy	Sell	R3	Buy	Sell
BH	-0,060%	NA	BH	0,044%	NA	BH	-1,36	NA
S1	-0,035%	-0,083%	S1	0,037%	0,051%	S1	-0,95	-1,62
S2	-0,043%	NA%	S2	0,016%	NA	S2	-2,65	NA
S3	0,020%	-0,052%	S3	0,038%	0,060%	S3	0,53	-0,87

Table 36 - Risk and Returns analysis for Portugal Telecom
Source: The author

8.6.3. Statistical Validation: *T-test*

	T-Test **Buy Signals**	**Decision**	***T-Test*** **Sell Signals**	**Decision**	***T-Test*** **Buy-Sell Spread**	**Decision**
S1	0,451	Don't Reject	-0,383	Don't Reject	0,720	Don't Reject
S2	0,364	Don't Reject	NA	NA	NA	NA
S3	1,069	Don't Reject	0,085	Don't Reject	0,667	Don't Reject

Table 37 - *T-Test* for Portugal Telecom
Source: The author

NA: As investors do not trade the sell signals of S2 (they only exit positions) it is not possible to compute the measurements that rely on the daily return and variance of these signals.

8.7. Appendix F-S&P500 SPDR ETF

8.7.1. Characterization

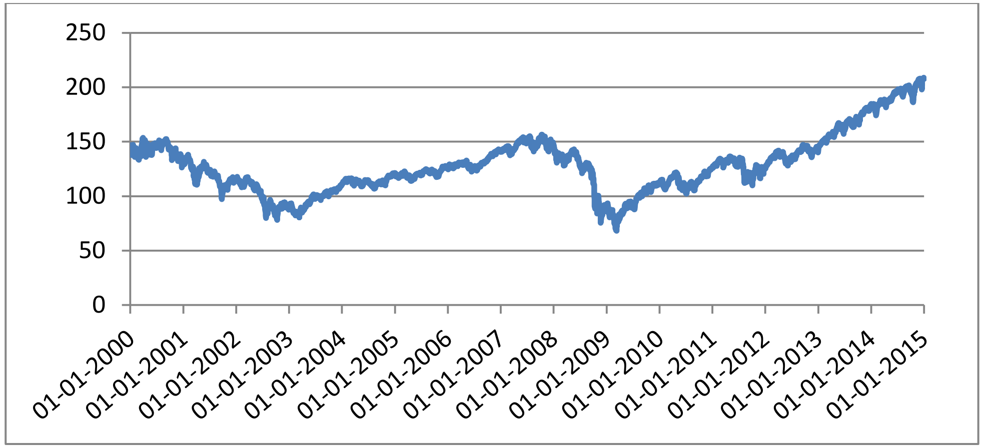

Figure 19 - Evolution of S&P500 SPDR ETF asset prices
Source: The author

	Outdays	# Buy Signals	# Sell Signals	# Days following Buy signals	# Days following Sell signals
S1	0	200	199	2146	1627
S2	1627	200	199	2146	0
S3	2553	106	89	635	585

Table 38 - Strategies Characterization
Source: The author

	# Profitable Buy Signals	# Profitable Sell Signals (S1 & S3)/ # Unprofitable Sell Signals (S2)	# Unprofitable Buy Signals	# Unprofitable Sell Signals (S1 & S3)/ # Profitable Sell Signals (S2)	Hit Ratio Buy	Hit Ratio Sell
S1	87	65	113	134	43,5%	32,7%
S2	87	134	113	65	43,5%	NA
S3	66	31	40	58	62,3%	34,8%

Table 39 - Strategies Characterization (Continuation)
Source: The author

8.7.2. Risk and Returns

Average Daily Returns	Buy	Sell	Average Daily Variance	Buy	Sell	R3	Buy	Sell
BH	0,009%	NA	BH	0,017%	NA	BH	0,55	NA
S1	-0,017%	0,043%	S1	0,012%	0,023%	S1	-1,43	1,86
S2	-0,025%	NA	S2	0,0114%	NA%	S2	-2,22	NA
S3	-0,032%	0,021%	S3	0,016%	0,038%	S3	-2,02	0,56

Table 40 - Risk and Returns analysis for S&P 500 SPDR ETF
Source: The author

8.7.3. Statistical Validation: *T-test*

	T-Test Buy Signals	Decision	*T-Test* Sell Signals	Decision	*T-Test* Buy-Sell Spread	Decision
S1	-0,824	Don't Reject	0,790	Don't Reject	-1,352	Don't Reject
S2	-1,102	Don't Reject	NA	NA	NA	NA
S3	-0,760	Don't Reject	0,146	Don't Reject	-0,562	Don't Reject

Table 41 - *T-Test* for S&P 500 SPDR ETF
Source: The author

NA: As investors do not trade the sell signals of S2 (they only exit positions) it is not possible to compute the measurements that rely on the daily return and variance of these signals.

8.8. Appendix G-Eurostoxx 50

8.8.1. Characterization

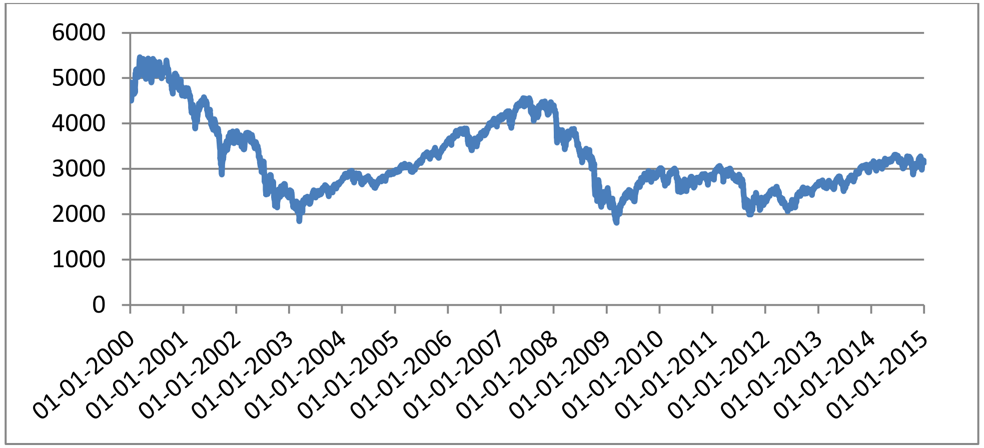

Figure 20 - Evolution of Eurostoxx 50 asset prices
Source: The author

	Outdays	# Buy Signals	# Sell Signals	# Days following Buy signals	# Days following Sell signals
S1	0	200	199	2156	1685
S2	1685	200	199	2156	0
S3	2589	100	89	660	592

Table 42 - Strategies Characterization
Source: The author

	# Profitable Buy Signals	# Profitable Sell Signals (S1 & S3)/ # Unprofitable Sell Signals (S2)	# Unprofitable Buy Signals	# Unprofitable Sell Signals (S1 & S3)/ # Profitable Sell Signals (S2)	Hit Ratio Buy	Hit Ratio Sell
S1	79	60	121	139	39,5%	30,2%
S2	79	139	121	60	39,5%	NA
S3	66	56	34	33	66,0%	62,9%

Table 43 - Strategies Characterization (Continuation)
Source: The author

8.8.2. Risk and Returns

Average Daily Returns	Buy	Sell	Average Daily Variance	Buy	Sell	R3	Buy	Sell
BH	-0,012%	NA	BH	0,023%	NA	BH	-0,50	NA
S1	-0,074%	0,069%	S1	0,017%	0,032%	S1	-4,45	2,17
S2	-0,066%	NA	S2	0,015%	NA	S2	-4,40	NA
S3	0,181%	-0,184%	S3	0,024%	0,044%	S3	7,38	-4,17

Table 44 - Risk and Returns analysis for Eurostoxx 50
Source: The author

8.8.3. Statistical Validation: *T-test*

	T-Test Buy Signals	Decision	*T-Test* Sell Signals	Decision	*T-Test* Buy-Sell Spread	Decision
S1	-1,687	Don't Reject	1,612	Don't Reject	-2,778	Reject
S2	-1,507	Don't Reject	NA	NA	NA	NA
S3	2,928	Reject	-1,917	Don't Reject	3,450	Reject

Table 45 - *T-Test* for Eurostoxx 50
Source: The author

NA: As investors do not trade the sell signals of S2 (they only exit positions) it is not possible to compute the measurements that rely on the daily return and variance of these signals.

8.9. Appendix H-Toyota

8.9.1. Characterization

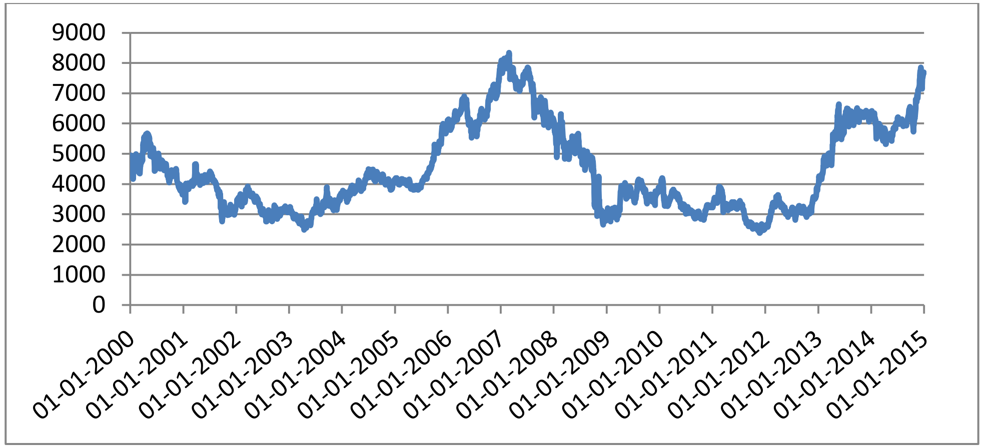

Figure 21 - Evolution of Toyota asset prices
Source: The author

	Outdays	# Buy Signals	# Sell Signals	# days following Buy signals	# days following Sell signal
S1	0	157	156	1926	1758
S2	1758	157	156	1926	0
S3	2604	76	71	599	481

Table 46 - Strategies Characterization
Source: The author

	# Profitable Buy Signals	# Profitable Sell Signals (S1 & S3)/ # Unprofitable Sell Signals (S2)	# Unprofitable Buy Signals	# Unprofitable Sell Signals (S1 & S3)/ # Profitable Sell Signals (S2)	Hit Ratio Buy	Hit Ratio Sell
S1	62	61	95	95	39,5%	39,1%
S2	62	95	95	61	39,5%	NA
S3	30	26	46	45	39,5%	36,6%

Table 47 - Strategies Characterization (Continuation)
Source: The author

8.9.2. Risk and Returns

Average Daily Returns	Buy	Sell	Average Daily Variance	Buy	Sell	R3	Buy	Sell
BH	0,013%	NS	BH	0,038%	NA	BH	0,34	NA
S1	-0,029%	0,058%	S1	0,033%	0,043%	S1	-0,87	1,36
S2	-0,045%	NS	S2	0,032%	NA	S2	-1,41	NA
S3	0,008%	0,067%	S3	0,042%	0,061%	S3	0,20	1,09

Table 48 - Returns and Risk analysis for Toyota
Source: The author

8.9.3. Statistical Validation: *T-test*

	T-Test Buy Signals	Decision	*T-Test* Sell Signals	Decision	*T-Test* Buy-Sell Spread	Decision
S1	-0,791	Don't Reject	0,772	Don't Reject	-1,347	Don't Reject
S2	-1,110	Don't Reject	NA	NA	NA	NA
S3	-0,048	Don't Reject	0,461	Don't Reject	-0,416	Don't Reject

Table 49 - *T-Test* for Toyota
Source: The author

NA: As investors do not trade the sell signals of S2 (they only exit positions) it is not possible to compute the measurements that rely on the daily return and variance of these signals.

8.10. Appendix I-USD/JPY

8.10.1. Characterization

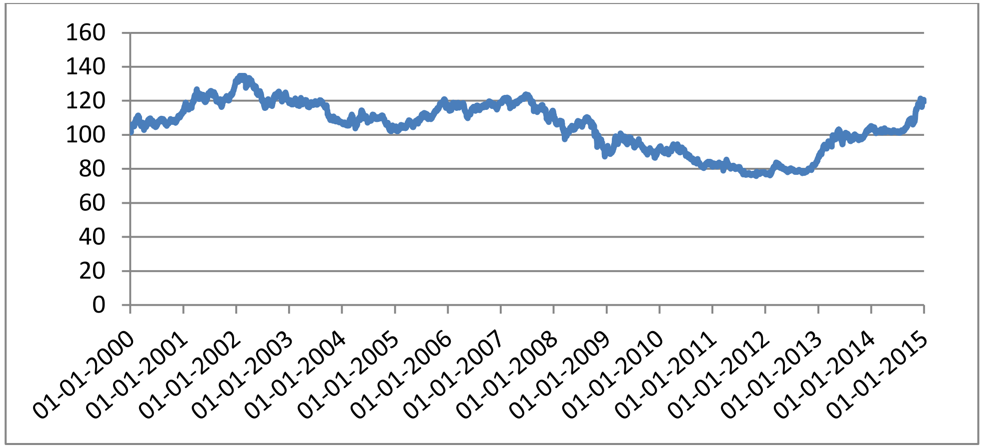

Figure 22 - Evolution of USD/JPY asset prices
Source: The author

	Outdays	# Buy Signals	# Sell Signals	# Days following Buy signals	# Days following Sell signals
S1	0	176	177	1993	1920
S2	1920	176	177	1993	0
S3	2272	112	100	848	793

Table 50 - Strategies Characterization
Source: The author

	# Profitable Buy Signals	# Profitable Sell Signals (S1 & S3)/ # Unprofitable Sell Signals (S2)	# Unprofitable Buy Signals	# Unprofitable Sell Signals (S1 & S3)/ # Profitable Sell Signals (S2)	Hit Ratio Buy	Hit Ratio Sell
S1	68	65	108	112	38,6%	36,7%
S2	68	112	108	65	38,6%	NA
S3	49	38	63	62	43,8%	38,0%

Table 51 - Strategies Characterization (Continuation)
Source: The author

8.10.2. Risk and Returns

Average Daily Returns	Buy	Sell	Average Daily Variance	Buy	Sell	R3	Buy	Sell
BH	0,004%	NA	BH	0,004%	NA	BH	0,98	NA
S1	0,009%	-0,001%	S1	0,004%	0,005%	S1	2,37	-0,21
S2	0,007%	NA	S2	0,003%	NA	S2	2,07	NA
S3	0,011%	0,004%	S3	0,004%	0,006%	S3	2,79	0,66

Table 52 - Risk and Returns analysis for USD/JPY
Source: The author

8.10.3. Statistical Validation: *T-test*

	T-Test **Buy Signals**	Decision	***T-Test*** **Sell Signals**	Decision	***T-Test*** **Buy-Sell Spread**	Decision
S1	0,279	Don't Reject	-0,268	Don't Reject	0,473	Don't Reject
S2	0,180	Don't Reject	NA	NA	NA	NA
S3	0,297	Don't Reject	-0,002	Don't Reject	0,205	Don't Reject

Table 53 - *T-Test* for USD/JPY
Source: The author

NA: As investors do not trade the sell signals of S2 (they only exit positions) it is not possible to compute the measurements that rely on the daily return and variance of these signals.

8.11. Appendix J-Gold

8.11.1. Characterization

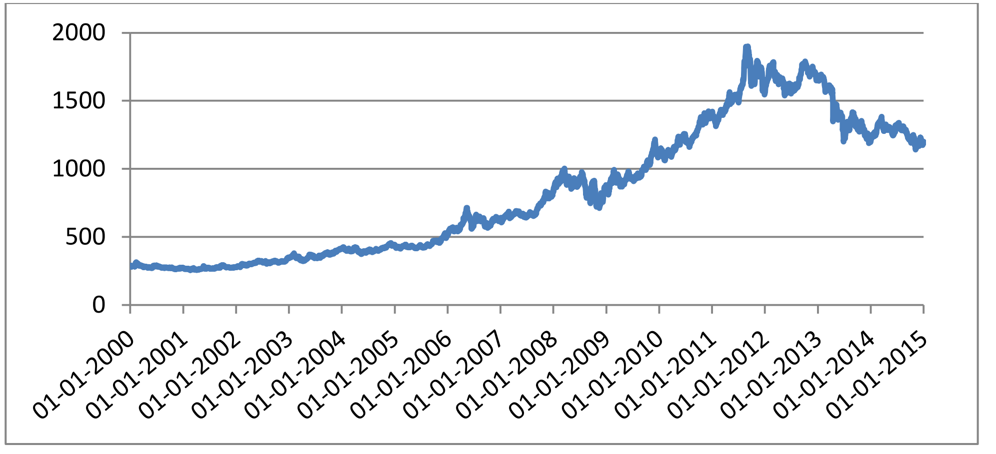

Figure 23 - Evolution of Gold asset prices
Source: The author

	Outdays	# Buy Signals	# Sell Signals	# Days following Buy signals	# Days following Sell signals
S1	0	176	177	2117	1794
S2	1794	176	177	2117	0
S3	2322	112	107	866	725

Table 54 - Strategies Characterization
Source: The author

	# Profitable Buy Signals	# Profitable Sell Signals (S1 & S3)/ # Unprofitable Sell Signals (S2)	# Unprofitable Buy Signals	# Unprofitable Sell Signals (S1 & S3)/ # Profitable Sell Signals (S2)	Hit Ratio Buy	Hit Ratio Sell
S1	82	68	94	109	46,6%	38,4%
S2	82	109	94	68	46,6%	NA
S3	54	40	58	67	48,2%	37,4%

Table 55 - Strategies Characterization (Continuation)
Source: The author

8.11.2. Risk and Returns

Average Daily Returns	Buy	Sell	Average Daily Variance	Buy	Sell	R3	Buy	Sell
BH	0,036%	NA	BH	0,013%	NA	BH	2,75	NA
S1	0,034%	0,039%	S1	0,013%	0,014%	S1	2,72	2,79
S2	0,038%	NA	S2	0,006%	NA	S2	5,99	NA
S3	0,002%	0,068%	S3	0,015%	0,018%	S3	0,15	3,85

Table 56 - Risk and Returns analysis for Gold
Source: The author

8.11.3. Statistical Validation: *T-test*

	T-Test Buy Signals	Decision	*T-Test* Sell Signals	Decision	*T-Test* Buy-Sell Spread	Decision
S1	-0,068	Don't Reject	0,074	Don't Reject	-0,123	Don't Reject
S2	0,053	Don't Reject	NA	NA	NA	NA
S3	-0,746	Don't Reject	0,595	Don't Reject	-1,012	Don't Reject

Table 57 - *T-Test* for Gold
Source: The author

NA: As investors do not trade the sell signals of S2 (they only exit positions) it is not possible to compute the measurements that rely on the daily return and variance of these signals.