The Effect of Stock Characteristics on Technical Analysis Profitability: the Portuguese Stock Exchange case

By

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Biographical Note

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Abstract

Many of the existing literature and recent-made enquiries state that technical analysis, whose goal is to predict the future evolution of asset prices from the observation and the use of their historical prices and trading volumes, is a growing investing technique used by many on the investors/traders community, being in the middle of a debate that attracted the attention and interest of both investors and academics for many decades. This study aims to contribute to the ongoing discussion, making an investigation about technical analysis trading rules profitability in the Portuguese Stock Market. Our principal aim is studying if certain stock characteristics (like size, liquidity, volatility and the stock´s industry) have a relevant influence on its results. Our time frame is between 2003 and 2013 and we've considered 38 stocks present in the Portuguese stock market and the PSI 20 index itself.

We've found that technical analysis based investing models are not always statistically profitable, but, when they are, they produce substantial profits, even after transaction costs. There is some evidence that they are more profitable for less liquid stocks and more volatile stocks. There is no evidence to any industry or size bias in our study.

Our conclusions can have enormous practical implications for investors and traders as they can decide to which extend it is advisable, or if it is advisable at all, to rely on technical analysis when making their investment decisions, and in what type of stocks to use it. Similar studies have been done but never for the Portuguese Stock Exchange, nor the selected time frame.

Key-words: Financial Markets, Stock Markets, Technical Analysis, Portuguese Stock Market, Stock Characteristics.

JEL-Codes: G10; G11; G14; G15; G23

Resumo

A maioria da literatura existente sobre este tema aponta a análise técnica, cujo principal objectivo é a previsão da evolução futura do preço dos activos, através da observação dos seus preços históricos e volumes, é uma técnica de investimento crescentemente usada pelos investidores/*traders*, estando no meio de um debate que atrai a atenção quer de investidores, quer de académicos por muitas décadas. Este estudo visa contribuir para a corrente discussão, investigando a possibilidade de modelos baseados em regras de análise técnica se verificarem lucrativos no mercado accionista português, com o principal objectivo de averiguar se certas características das acções, como o seu tamanho, liquidez, volatilidade e a indústria em que estão inseridas, influenciam de alguma forma os seus resultados. Estudamos tal questão em 38 acções transaccionadas em Portugal, bem como no índice PSI 20, no tempo compreendido entre 2003 e 2013.

Concluímos que modelos de investimento baseados em análise técnica nem sempre demonstram ser estatisticamente lucrativos, mas, quando assim o é, produzem lucros substanciais. Existe evidência de melhores resultados em acções ilíquidas e mais voláteis, não existindo ligação entre os mesmos resultados e a indústria em que a acção se insere e o seu tamanho.

As conclusões aqui apresentadas poderão ter enormes implicações para quem pretenda investir no mercado bolsista, visto que permitem decidir se é, e até que ponto é, compensatório seguir modelos de investimento com base em regras de análise técnica, e em que tipo de acções os utilizar. Estudos similares foram realizados, mas nunca para o mercado accionista português, nem para o período temporal considerado.

Palavras-chave: Mercados Financeiros, Mercados Accionistas, Análise Técnica, Mercado Bolsista Português, Características de Acções;

Códigos JEL: G10; G11; G14; G15; G23

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1. Introduction

Technical analysis can be seen as "an art", according to Pring (2002), with the main objective of "identify a trend reversal at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed". In fact, technical analysis is a forecasting method of price movements using past prices, volume and, in case of future markets, open interest (Park and Irwin, 2004). Many previous studies show the relevance of this analysis in the real world of investing decisions, with Bray (2002) stating that 35% of all the volume on the New York Stock Exchange (NYSE) is due to technical trading rules, and Talley (2002) suggesting that the doubts that investors have about the integrity of the accounting data that generates fundamental analysis indicators are leading technical analysis to become even more popular.

With so many interest showed by investors and traders, the academic community soon started studying technical analysis as a whole investment technique and stock picking tool, with a strong focus on whether it has proven to be a profitable investment strategy. Brock *et al.* (1992), Bessembinder and Chan (1998) or Coutts and Chen (2000) are all examples of studies that investigate technical analysis profitability in indexes like the Dow-Jones Industrial Average (DIJA), or the Hang Seng Index (HSI). Park and Irwin (2004) made an extensive review on the evidence of profitability of technical analysis, categorizing the analyzed studies in "early" and "modern" groups, according to the characteristics of testing procedures.

However, only Marshall *et al.* (2009) studied the effect that certain stock characteristics, specifically size, liquidity or industry, have on the possible profits gave by the application of technical trading rules, focusing on the US stock market. Our study aims to analyze, not only the technical analysis profitability, but mainly the effect that certain stock characteristics, namely the size (measured by market capitalization), liquidity (measured by the turnover), volatility (measured by the stock standard deviation), and the industry where the stock is inserted, have on technical analysis profits, between the years 2003 and 2013, for the stocks quoted on the Portuguese Stock Exchange. The time frame will be divided into two groups (2003- July 2007 and July 2007-2013) in order to see if the fact that the market is in its *bull* or *bear* state has any influence in possible profits generated by technical analysis trading rules.

In order to reach this goal, we define a sample of the vast majority of stocks listed in the Portuguese Stock Exchange (PSI *Geral* index), and construct two investing models that includes three main technical rules/indicators each, in order to obtain a full insight on technical analysis profitability, rather than individually testing one simple trading rule. We then perform the necessary statistical tests to see if the chosen technical trading models produced profitable results in the given time interval. Then, we will divide the stocks of our sample into sub-samples according to the chosen characteristics, and test if those same characteristics have any impact in the models profitability. We also compare the model´s results with other strategies, like a "buy-and-hold" one, and test if it produced positive results on the PSI 20 index (the most relevant indicator of the Portuguese stock market) itself.

Besides this section, this dissertation proposal is structured as follows: in the next section, section 2, we will present a literature review of the topic. In section 2.1 we will present the birth and origins of technical analysis, in section 2.2 the efficient market hypothesis and its relation with technical analysis, in section 2.3 the studies made on technical analysis profitability. Section 2.4 addresses the relation between technical analysis and behavioral finance, section 2.5 gives a quick overlook on the Portuguese Stock Market and its efficiency, section 2.6 makes a review of the similar studies and their conclusions, and lastly, in section 2.7, a final critical analysis of the reviewed literature will be discussed.

In section 3, we will disclose the methodological aspects of this study, specifying in section 3.1 the data that will be used, in section 3.2 the technical trading rules that we will analyze/test and that will constitute our model, in section 3.3 the chosen stock characteristics description and in section 3.4 the statistical tests/approach that we will use.

Section 4 will have the empirical results. First, in section 4.1, our hypothetical investor assumptions will be revealed, then, on section 4.2, we will we will present a descriptive analysis of the sample in which we will work upon, followed by section 4.3, in which we will present our models application results, and by section 4.4, which will contain the tests to verify the existence of the transaction costs significance. Lastly, on section 4.5, we will present the tests and assumptions that will lead to our conclusions about the influence of stocks characteristics on technical analysis profitability. To finish this dissertation, we will present, in section 5, the conclusions and the future research suggestions.

2. Literature Review

As defined in the previous chapter, technical analysis is an approach to predict future market price movements based on the identification of patterns in prices, volume and other market statistics. Its main idea is that we can predict future price movements from past prices. With this goal, it employs a number of techniques, the most common of which are *charts*, *trading rules* and *cycle analysis*. A considerable amount of literature has been published on this subject. Even so, there is no discernable consensus over its role, with opinions of this technique as a forecasting mechanism being very controversial. On this chapter, we will review the most important topics on technical analysis, as well as mentioning the most relevant papers on the area.

2.1 Birth and Origins of Technical Analysis

The origin of technical analysis dates back to at least the 18th century, when the Japanese developed a form of predicting future prices known as candlestick charting techniques. However, this was a very primitive technique, and, according to Nilson (1991), was not introduced to the West until the 1970s. Despite these first techniques, the birth of technical analysis is considered to be in the late 1800s, with the Dow Theory developed by Charles H. Dow, as described on Cesari and Cremonini (2003). While more than 100 years old, the Dow Theory remains the foundation of much of what we know today as technical analysis, Ray (2012).

His theory was formulated from a series of *Wall Street Journal* editorials which reflected Dow's beliefs on how the stock market behaved. This theory still exists, despite modified in many forms, and is well known and accepted in the field of technical analysis. It‘s based on the following six axioms, described on Rhea (1932): *1)* price evolves in trends (where we can identify *primary*, *secondary* and *tertiary* trends); *2)* we distinguish three phases of primary trend (phase of *accumulation*, phase of *participation* and the phase of *distribution*); *3)* the price reflects all available (knowable) information and the opinions of all market participants regarding that information; *4)* the averages must support each other (Dow built two averages - the *Industrials* and the *Rails*); *5)* the volume must confirm the trend; and *6)* trends exist until definitive signals prove they have ended.

Despite its popularity, the Dow Theory faces different criticisms. Kirkpatrick and Dahlquist (2011) point the delayed signal to buy or sell, as the theory does not recognize a turn until long after it has occurred and has been confirmed, and the fact that the different trends are not strictly defined, which brings difficulty in trend determination in case of price fluctuation, as two main critiques to it. Although currently its relevance as a stand-alone analytical technique has weakened, a quick reference is more than justified in a study with this purpose.

2.2 Efficient Market Hypothesis and Technical Analysis

Since the beginning of the academics interest on financial markets, many studies have been conducted to obtain a theoretical foundation to understand how asset prices will evolve. Perhaps the most famous and widely used hypothesis was defined by Fama (1970) and is known as the Efficient Market Hypothesis (EHM). It is a milestone in modern finance theory and has served as the theoretical fundament for many modern finance models and tools. The EMH is generally expressed in three separate forms as refined by Jensen (1978): *Weak* (that suggests that current security prices instantaneously and fully reflect all information contained in the past history of security prices), *Semi-strong* (which states that security prices instantaneously and fully reflect all publicly available information about the securities market), and *Strong* (that says that current security prices instantaneously and fully reflect all known information about the securities markets including that which is privately available (inside information)). For the purpose of this dissertation we will primarily focus on weak-form EMH given its relationship with technical analysis.

Its main assumption is that stock prices follow a “random walk”, so we do not and cannot know what their next movement will be. It also states that security prices fully reflect all available information, so new information will thereby immediately be incorporated in the price, making the quoted stock price a fair value. According to Jensen (1978), no one can expect to gain any abnormal profit for a given risk for a longer period of time. New information is by definition unpredictable, making the stock price and the return unpredictable and random.

For this weak form of efficiency to hold, and to be proven truth, technical analysis must reveal not to be a profitable strategy, compared to a buy-and-hold strategy, in any studied country, in any time frame and in any of its trading rules and methods. In the next section we will discuss this topic, accessing whether technical analysis is, or isn't, profitable.

2.3 Technical Analysis Profitability

In this section, we will analyze technical analysis profitability, starting by the work of Park and Irwin (2004), which reviews a total of 92 studies, published from 1988 to 2004, on technical analysis profitability, not only for stock markets, but also for currency and future markets. The authors found positive evidence on the profitability of technical analysis, with 58 studies, among the 92, showing positive results regarding technical analysis based strategies. The majority of the analyzed studies reveal profitable results in the three considered types of markets. Still, most empirical studies appeared to be subject to problems in their testing procedures, such as data snooping, ex post selection of trading rules, and difficulties in the estimation of risk and transaction costs.

A milestone study and one of the most influential in this area was the one made by Brock *et al.* (1992), as it used a very long price history and, for the first time, model-based bootstrap methods for making statistical inferences about technical trading rules peofitability. They tested 26 technical trading rules, based on two simple technical trading systems, a moving average-oscillator and a trading range breakout (resistance and support levels), on the Dow Jones Industrial Average (DIJA), between the years of 1897 and 1968. It was proved that the tested trading rules out-performed a buy-and-hold strategy. However, the gross returns of each trading rule were calculated without taking into account trading costs, with no evidence of economic profits being presented. A few years later, in 1998, Bessembinder and Chan evaluated the same 26 trading rules as Brock *et al.* (1992), but this time including dividend payments and transaction costs, showing that these subsume the profitability documented by the previous study.

Many other studies with the same and different testing approaches were already done for virtually every stock market in the world, producing overall mixed results. On one hand, studies like Hrušová (2011), that tested MACD and RSI indicators in seven central and eastern European stock markets and concluded that technical analysis indicators produced significantly positive returns on most of them, like Isakov and Hollistein (1999), which conclude that with a rule of double moving average with averages computed on one and five days, an annual average return on the Swiss stock exchange of 24.30% is obtained, compared to a buy-and-hold annual return of 6.25%, or like Lento (2007), that tested the effectiveness of nine technical trading rules in eight Asian-Pacific equity markets, and concluded that those rules were profitable, even after transaction costs, on six of the studied markets. On the other hand, studies like Coutts and Cheng (2000) for the Hang Seng index, Hudson *et al.* (1996) for the FTSE 30 index, and Pirisi and Vasquez (2000) for Chilean indices, find that the frequent trading required by each technical trading rule leads to transaction costs that erode any profits generated by them. Marshall *et al.* (2010) concluded that over 5000 popular technical trading rules are not consistently profitable in the 49 country indices that comprise the Morgan Stanley Capital Index once data snooping bias is accounted for. The study also found that there is some evidence that technical trading rules perform better in emerging markets than developed ones, which is consistent with the finding of previous studies which state that these markets are less efficient.

In Portugal, the study of technical analysis profitability is still an under developed topic, with few studies on it. Silva (2001) was one of the first authors to study this topic, testing moving average rules and support and resistance levels for the BVL index between the years of 1988 and 2000, concluding that, even after transaction costs, the tested rules generated profits of 5.98% annually, when compared with a simply buy-and-hold strategy. Recently, Osório (2010) tested the MACD and RSI indicators for the PSI 20 index for the years from 2001 to 2009, concluding that the MACD indicator produced profits above market averages and that the same didn’t happen with the RSI indicator that couldn´t beat a buy-and-hold strategy. Pereira (2011) tested rules like the exponential moving average (EMA), Bollinger bands and the RSI for the PSI 20 index and for twelve individual stocks quoted in that index, with data between the years of 1993 and 2010, concluding that, after transaction costs, the tested rules generated statistically significant profits in the index and in all except one individual stocks considered, and that the market did not prove to be efficient in the weak form of Fama.

2.4 Behavioral Finance and Technical Analysis

Many of the technical analysis bases can be traced back and connected to behavioral finance principles, as in behavioral and in technical theory we observe a combination between fundamental (rational) and psychological - emotional (irrational) factors, Vasiliou *et al.* (2008). In recent years it has become more and more obvious that psychology factors play an extremely important role in financial markets, driving back the influence on the rational actions of stock market participants. Behavioral Finance is a young field, with its formal beginnings in the 1980s, incorporating insights from other social sciences, such as psychology and sociology into finance economics, attempting to explain anomalies that defy standard economic analysis, according to Shiller (2003). This field of Finance is showing that in an economy where rational and irrational traders interact, “irrationality” can have a substantial and long-lived impact on prices, particularly in stock ones, Barberis (2003).

The intersection between the literature on individual investors and the literature on technical analysis is sparse. However, many of the recent literature tries to identify common elements in technical and behavioral theory, for instance: according to Grinblatt & Keloharju (2000), cultured investors in the Finish Stock Market were more likely to follow momentum-trading strategies; Barber and Odean (2001) and Odean (1999) find that individual investors trade excessively, exposing themselves to a high level of risk; Odean (1998) finds that individual investors demonstrate a significant preference for selling winners and holding losers, confirming the disposition effect. Investors who are overconfident believe they can obtain large returns, thus they trade often and they underestimate the associated risks (Kyle and Wang, 1997); Coval and Shumway (2002) find that traders suffer from a loss-aversion bias. Very recently, Hoffmann and Shefrin (2014) , based on a study carried out by Lewellen *et al.* (1980), found that individual investors who use technical analysis and trade options frequently make poor portfolio decisions, resulting in dramatically lower returns than other investors, as they disproportionately prone to have speculation on short-term stock-market developments as their primary investment objective, hold more concentrated portfolios which they turn over at a higher rate, are less inclined to bet on reversals and choose risk exposures featuring a higher ratio of nonsystematic risk to total risk.

2.5 The Portuguese Stock Market and its Efficiency

The Portuguese Stock Exchange had its origins on 1 of January 1769, when the Lisbon Stock Exchange was created. Almost one century later, the Porto Stock Exchanged was born. Both exchanges merger in 1999, becoming the *Bolsa de Valores de Lisboa e do Porto,* and join the Euronext family in 2007, being now known as the *Euronext Lisbon* Stock Exchange. Its benchmark index is the PSI 20. The PSI 20 is a free float market capitalization weighted index that reflects the performance of the 20 (18 nowadays) most actively traded shares listed on Euronext Lisbon, and is the most widely used indicator of the Portuguese stock market. It serves also as an underlying for structured products, funds, exchange traded funds and futures. It was introduced on 31 December 1992, and is constituted by stocks from every sector, like utilities, oil and gas, retail or banks. Despite being the main one, other indices exist in the Portuguese Stock Exchange besides the PSI 20. The PSI 20 NR (with NR standing for Net Return, this index is issued since the end of 2010, and is obtained by reinvesting the net dividend, which is equal to the ordinary gross dividend minus the amount of withholding tax), the PSI 20 GR (the GR stands for Gross Return, with this index being published since 1992 and being obtained by reinvesting in the index the ordinary gross dividends declared by the index constituents) and the PSI *Geral* (also called PSI All-Share) are examples of that. Sectorial indices like the PSI Utilities, PSI Technology or the PSI Financial, which only comprise stocks of the respective sectors, are also available. The Psi *Geral* index will serve as base for this study. It is a market capitalization weighted price index of the eligible companies listed on the Euronext Lisbon. It includes shares issued by all the companies which are listed on Euronext Lisbon. On the last day of 2013, 58 companies were quoted on that stock exchange.

Afonso and Teixeira (1999) were the first to test the Fama´s weak-form of efficiency on the Portuguese stock market, from the time frame between 1990 and 1997. They concluded that the possibility of having abnormal profits in the stock market existed, putting in question the form of efficiency tested. A few years later, Nascimento (2007) tested if the *random walk* model could be applied to the Portuguese stock market, with data from 1997 to 2007. The study produced mixed results, as the prices followed a random walk (which corroborates the market efficiency hypothesis) in a selected time period, nor following it in the remaining time, which suggest some predictability in prices variation. Recently, Borges (2010) tested the weak-form market efficiency applied to stock market indexes of France, Germany, UK, Greece, Portugal and Spain, from January 1993 to December 2007, using a serial correlation test, a runs test, an augmented Dickey-Fuller test and the multiple variance ratio test, for the hypothesis that the stock market index follow a random walk. The author concluded that the studied hypothesis is rejected for Greece and Portugal, due to serial positive correlation. However, the empirical tests show that these two countries have also been approaching a random walk behavior after 2003, which can indicate an increase in efficiency levels. Based on that work, Vaz (2012) also tested the Fama´s weak-form of market efficiency, applied to the same six European market indexes from January 2007 to January 2012. The author designed a strategy based on the k-NN and on the Neural Network predictions, and concluded that it would be possible to obtain significantly higher earnings by the implementation of this strategy than using a simple buy-and-hold strategy. Being so, this shows that the PSI-20 is not yet totally efficient. Our study will also contribute to this ongoing debate.

2.6 Similar studies and their conclusions

As we have seen in section 2.3, many studies exist on technical analysis profitability (with an even bigger number that is not here referenced), focusing on both Portuguese and international stock markets. However, as mentioned in the introduction, the main research question of this dissertation is a broader one. It aims to analyze, not only the technical analysis profitability, but mainly the effect that certain stock characteristics, such as the size, liquidity and volatility, have on technical analysis profits, for stocks quoted on the Portuguese stock exchange. The only study made with such specifications was Marshall *et al.* (2009). In it, the authors studied the effect that certain stock characteristics, like size, liquidity or industry where the stock is inserted, have on the possible profits gave by the application of technical trading rules, focusing on US stock markets, namely the New York Stock Exchange (NYSE) and the National Association of Securities Dealers Automated Quotations (NASDAQ), from the years of 1990 to 2004. They picked stocks listed both at the beginning and the end of the time period in order to keep the methodology manageable, with a maximum yearly nontrade percentage of less than 5% over all years. The final sample contained 1065 stocks, 866 quoted on the NYSE and 199 on NASDAQ. The technical trading rules tested were the Variable-length Moving Average (VMA), the Fixed-length Moving Average (FMA) and the Trading Range Break-out rule (TRB). For each type of rule the short term is set at 1 trading day, and the long-term at 50, 100, 150 and 200 trading days.

After defining the sample and the rules to be tested, the authors applied a *bootstrapping* methodology, originated by Efron (1979), using the GARCH-M (Generalized Autoregressive Conditionally Hetroskedastic in the Mean) as the model for modeling the stock price process. Bootstrapping has found relevance in numerous statistical procedures and has become a widely accepted alternative to traditional statistical inference. It is used to address the possible problem of non-normality of returns. Testing statistical significance in this way can assure that the results found are robust. The results were run assuming investment at the closing prices on both the signal day and the following day. The study concluded that the number of statistically significant positive return companies is small for all trading rules over all periods for both markets. On average, the trading rules give positive results on only 2.8% of NYSE stocks and 3% of NASDAQ stocks. After this first conclusion, the authors study more in-depth the stocks that revealed to be profitable, generating *t*-statistics by comparing the size and liquidity of the stocks which generate positive significant returns to those which do not. The results, for all trading rules, indicate that smaller size and smaller volume stocks are more likely to generate positive statistically significant return than larger size and larger volume stocks. The analysis by industry showed that the number of significantly positive stocks was randomly spread across the different industries, not existing a link between a firm´s industry and the profitability of technical analysis. Lastly, the authors tested the stocks that revealed to be profitable for economic significance, concluding that, even after transaction costs, when technical trading rules do generate profits, the profits are substantial, largely beating a simple buy-and-hold strategy, which can be the reason explaining why practitioners continue to use these trading rules despite them not generating profits on a consistent basis.

2.7 Critical analysis of the reviewed literature

Since its birth, by the hands of Charles Dow in the late 1800´s, technical analysis has always been looked at with disdain by many scholars and academics, and paradoxically has been used as a main investment technique by many traders and investors. Many have attacked it, using the Efficient Market Hypothesis argument or the *random walk* of stock prices as an explanation of why technical analysis based investment strategies cannot generate any substantial profits, like Bessembinder and Chan (1998). Numerous studies have been made that show, in fact, that technical trading rules do not produce above-market profits (several studies mentioned on section 2.3), and, in many cases, after transaction costs, are even beat by a simple buy-and-hold strategy. However, countless other studies have been made to prove the contrary, showing that technical analysis, in almost all stock exchanges and during all possible time periods, through the use of some technical rules, generate profits in scenarios where otherwise wouldn´t be possible. Portugal is not an exception to this type of studies, with technical indicators being studied and most of them revealed to be profitable, questioning also the efficiency of the Portuguese Stock Market. The heated debate that surrounds these questions, both the technical analysis profitability and the efficiency of the Portuguese Stock Exchange justifies, *per si*, the realization of this study.

Only one study with the same research topic as the one we are conducting have been made, but focusing on the US stock market, making this topic and consequent underlying questions a research hole in Portugal, fact that arises the need for this new study.

3. Methodological Aspects

This section intends to expose the data used in this study and the methodology adopted. Along it, we will present the data in which we will work on, the technical trading rules and the stock characteristics that will be tested/analyzed, as well as the methodological steps that we will follow in order to reach our final results, including all the assumptions and tests made.

3.1 Data

Our study is centered in the Portuguese stock market – NYSE Euronext Lisbon, more specifically in the stocks that integrate the PSI *Geral* index. The sample period runs from January 1st 2003, the first trading day of that year, to December 31st 2013, exactly 11 years. We will use the data present at *Thompson Reuters Datastream* database, consisting of a time series of daily stock prices at closing time. Base on those prices, we will extract information like the daily returns of each stock. For a specific stock to be included in our sample, it must belong to the PSI *Geral* during the years that we will test, and be active at the end of our sample, which makes a total of 58 stocks. Of those 58 stocks, to keep the methodology manageable and have statistical relevant results, we will exclude those that have less than two years of trading, and those that do not have sufficient trading activity to be of interest to traders in general, i.e., stocks that are not traded on, at least, 50% of the days of our time interval. The final number of included stocks is 38, since there are several stocks in the Portuguese exchange that fail the trading activity criteria. The list of stocks to analyze will then be, presented in alphabetical order:

Name	Code	Name	Code
ALTRI	ALT(P)	BANCO COMERCIAL PORTUGUES	BCP(P)
BANCO BPI	BPI(P)	CIMENTOS DE PORTUGAL	CPR(P)
CIPAN	CIP(P)	COFINA	CFNA(P)
COMPTA	COM(P)	CORTICEIRA AMORIM	COR(P)
EDP ENERGIAS	EDP(P)	F RAMADA	RINT(P)

DE PORTUGAL		INVESTIMENTOS	
FUTEBOL CLUBE DO PORTO	FCP(P)	GALP ENERGIA	GES(P)
GLINTT GLOBAL	GLIN(P)	IBERSOL	IBE(P)
IMPRESA	IMPR(P)	INAPA	INA(P)
JERONIMO MARTINS	JMT(P)	LISGRAFICA	LIG(P)
MARTIFER	MAR(P)	MOTA ENGIL	EGL(VO)
NOS	NOS(P)	NOVABASE	NBA(P)
PORTUCEL EMPRESA	PTI(P)	PORTUGAL TELECOM	PTC(P)
REDITUS	RED(P)	REN	REN(P)
SAG GEST	GST(P)	SDC INVESTIMENTOS	SCO(P)
SEMAPA	SEM(P)	SONAE CAPITAL	SNC(P)
SONAE COM	SNCA(P)	SONAE INDUSTRIA	SOI(P)
SONAE	SON(P)	SPORT LISBOA E BENFICA FUTEBOL	SLB(P)
SPORTING CLUBE DE PORTUGAL	SCP(P)	SUMOL+COMPAL	SUCO(P)
TEIXEIRA DUARTE	TDSA(P)	VISTA ALEGRE ATLANTIS	VAFK(P)

Table 1 - Stocks that constitute our sample and will be under analysis in our study. The code refers to the Thompson Reuters Datastream code.

Each included stock can have a different number of observations, as not all started to be traded on the same day. However, the maximum number of observations that any individual stock can have is 2870. We will also test the profitability of our model in the PSI 20 index itself, so we will use the index values for the same time frame, in order to also get data like the daily returns.

The use of the above described process to select our sample will minimize problems like the *forward-looking bias* i.e. information that is available ex-post will not be used, the *delisting bias*, the situation where a stock is getting delisted during a period under study emerges and the *survivorship bias*, a situation that arises when a portfolio is constructed on the basis of the companies that have survived the time period of the test and are available for portfolio construction. We will also avoid troubles associated with *data snooping*, as this study does not search for trading rules proved to be profitable in the past but set the trading rules together with all the parameters in advance instead.

We will also break down our time frame into two sub-periods: the first one between January 1st 2003 and July 17th 2007 (with each stock having a maximum of 1185 observations), and the second one between July 18th 2007 and December 31st 2013 (with each included stock having a maximum 1685 observations), in order to see if the fact that the market is in its *bull* or *bear* state had any influence in possible profits gave by technical analysis and on the purpose of our study. Bulls and Bears can be seen as two opposite market mentalities. Definitions of bull and bear markets can be different in small details, but all agree in the same assumptions. A market can be considered to be on a *bull* stage when it is in a sustained period of positive market returns, achieving new highs and being characterized as a period of wealth creation. On the other hand, a *bear* market is a sustained period of negative market returns resulting in a substantial decline of wealth. Cooper *et al* (2004) define the market state as being "up" (bull in our case) when the preceding 3-year return has been positive and as "down" (bear) if the reverse is true. We will use July 17th 2007 as the splitting day between the two sub-samples, as it was the day where the PSI 20 index reached a pick of 13702 base points, reaching its higher value since the begging of our time sample, putting an end to the existing bull market phase, and marking the begging of a bear market, which would last until the end of our time sample.

3.2 Technical trading rules/model

Many trading rules have been tested before, as above mentioned. However, few studies have considered the impact of technical indicators when combined, i.e., many studies have studies if indicators like different length moving averages, MACD, the relative strength index, trading range breakout rules, etc, have proven to be, or not, profitable, but not many have done it using some of those rules together, to test their effect when combined. That is also a research hole for many stock exchanges across the world, as well for the Portuguese one. In this section we will describe the rules/indicators that will be considered in our model, and that will be tested.

3.2.1) Moving Averages

Among the most used trading rules by researchers to test market efficiency, the one employed most frequently is the so-called moving average (henceforth MA) rule. Due to the precise signals it generates, this rule is used by many investors as a stand-alone method, particularly in the automated trend following trading systems, and, in contrast to other rules of technical analysis, is mathematically well defined, in Neftci (1991).

It has many variations to it, as it is described in Pring (2002). In one of its versions, the *two non-centered*, moving averages with different length are initially created, a "short" moving average of order *n*, and "long" moving average of order *m* (with *m*>*n*), from the time series of stock prices or index levels, as defined as follows:

$$MAS_t = \left(\frac{1}{M}\sum_{i=0}^{M-1}\theta_i B^i P_t\right)$$

MAS_t represents the relatively shorter MA with length *m*;

$$MAL_t = \left(\frac{1}{N}\sum_{i=0}^{N-1}\theta_i B^i P_t\right)$$

MAL_t represents the relatively longer MA with length *n*, calculated at time t. In both moving averages Pt is the stock price at time t, θ_i are non-time varying parameters, and B is the backward shift operator, i.e. $B^i P_t = P_{t-i}$.

The MA rule generates a buy signal when MAS_t rises above MAL_t and when this happens, a trend is said to be initiated. On the opposite side, a sell sign is generated when MAS_t falls below the MAL_t. The most popular MA rule, as indicated in Brock et al. (1992), is the 1-200, which sets n=1 (so that MAS_t is just the current level of the stock price or index) and m=200. Although, lots of other rules can be constructed by modifying the values of *n* and *m*, such as the also popular 1-50, 1-150 or 2-200 rules. These rules are often modified by introducing a band around the MA, which reduces the number of buy and sell signals by eliminating "whiplash" signals that occur when MAS_t and MAL_t are close to each other. In our study, we will use the MA rules both with and without a one per cent band, i.e. a buy (sell) signal is generated when MAS_t is above (below) MAL_t by more than one per cent. If MAS_t is inside the band, no signal is generated. This rule attempts to simulate a strategy where traders go long as MAS_t moves above MAL_t and short when it moves below: with a band of zero all days are classified as either buys or sells.

Mathematically, buy and sell signals can be defined as following:

a) Buy Signals

$$\tau_j^B \equiv \inf\{t : t > \tau_j^B, MAL_t - MAS_t > DP_{t-1}\}$$

b) Sell Signals

$$\tau_j^S \equiv \inf\{t : t > \tau_j^S, MAS_t - MAL_t > DP_{t-1}\}$$

In both cases, the initial times τ^B_0 and τ^S_0 are set equal to zero and D is the so-called band, above described. All θ_i parameters will be set equal to one.

For the propose of our study, we will include in our model two moving average rules. We will use both short and long "longer averages". An argument for using shorter averages is that it is more in accordance with the time horizon for real investors. Investors usually measure their performance over a one year period and thus, try to maximize their profits in this period. A shorter moving average also captures the direction of the trend at an earlier stage. That being said, we will use the popular 1-200 rule (with no band), and a shorter "longer" moving average, the 1-50 rule (with an 1% band).

3.2.2) Stochastic

This technical indicator was developed by George C. Lane in the late 1950´s. It is basically a *momentum* indicator that shows the location of the close relative to the high-low range over a predefined number of periods. It compares an asset closing price to its price range over a given time period. Its underlying theory is that in a bullish market the highs are located closer to close values, being the opposite for a bear market true as well, as if the asset price tends to decrease, the lowest values are located near the close values. Hence, stochastic oscillator follows the speed or the momentum of prices instead of volume or prices themselves. Its main lead is the possibility of finding and identifying momentum changes direction before price ones.

It can also be used to identify Bull and Bear divergences. A bullish divergence is formed when price records a lower low, but the Stochastic Oscillator forms a higher low. This shows less downside momentum that could foreshadow a bullish reversal. On the other hand, a bearish divergence is formed when price records a higher high, but the Stochastic Oscillator forms a lower high. This shows less upside momentum that could foreshadow a bearish reversal.

The oscillator can be used in two ways: firstly, it is supposed to be useful for identifying overbought and oversold levels, and secondly, it can be used to identify bullish and bearish divergences to anticipate the change in price direction, as mentioned above. It consists of two lines which are expressed in the following formulas present on Lane (1984):

$$\%K = \frac{(\text{Close} - \text{Lowest Low})}{(\text{Highest High} - \text{Lowest Low})} * 100$$

Where, *Close* is current close value of the asset, *Lowest Low* is the lowest intraday value reached by the asset over the look-back period and *Highest High* is the highest intraday value reached by the asset over the look-back period.

The other line exploited in the stochastic oscillator is a three day simple moving average (SMA) of the line above, line known as %D, or the signal line.

The default setting for the Stochastic Oscillator is 14 periods, which can be days, weeks, months or an intraday timeframe, depending of the objective of the investor. A 14-period %K would use the most recent close, the highest high over the last 14 periods and the lowest low over the last 14 periods. In our study, the 14 periods are used which translates into 14 days, and 3 days SMA of the %K for the %D line.

There are three versions of the Stochastic Oscillator: the *Fast Stochastic Oscillator*, which is based on George Lane's original formulas for %K and %D, described above. However, %K in the fast version that appears rather choppy. In fact, Lane used %D to generate buy or sell signals based on bullish and bearish divergences. Because %D in the Fast Stochastic Oscillator is used for signals, *the Slow Stochastic Oscillator* was introduced to reflect this emphasis. The Slow Stochastic Oscillator smooths %K with a 3-day SMA, which is exactly what %D is in the Fast Stochastic Oscillator. There is also the *Full Stochastic Oscillator*, which is a fully customizable version of the Slow Stochastic Oscillator, with the %K being equal to the fast %K smoothed with X-period SMA, and the %D a X-period SMA of the previous found %K.

In our study, we will use a full stochastic oscillator, using a 3 days SMA to smooth the original %K. In fact, the full stochastic that we will use will be equal to a slow stochastic with 14 and 3 as the parameters.

As a bound oscillator, the Stochastic makes it easy to identify overbought and oversold levels. The oscillator ranges from zero to one hundred, no matter how fast a security advances or declines, this indicator will always fluctuate within this range. The original settings use 80 as the overbought threshold and 20 as the oversold threshold. These levels can be adjusted to suit analytical needs and security characteristics. Readings above 80 would indicate that the underlying security was trading near the top of its high-low range. Readings below 20 occur when a security is trading at the low end of its high-low range.

There are three basic techniques for using the various Stochastic Oscillators to generate trading signals: *crossovers*, *divergence* and *overbought/oversold conditions*. In terms of crossovers, we can have a %K line / %D line crossover, which states that a buy signal occur when the %K line crosses above the %D line and a sell signal occurs when the %K line crosses below the %D line, or a %K line / 50-level crossover, that says that when the %K line crosses above 50 a buy signal is given and, alternatively, when the %K line crosses below 50, a sell signal is given. Also, looking for divergences between the Stochastic Oscillator and the asset's price can prove to be very effective in identifying potential reversal points in price movement. A buy signal can be identify on a classic bullish divergence: lower lows in price and higher lows in the Stochastic Oscillator, and a short signal on classic bearish divergence: higher highs in price and lower highs in the Stochastic Oscillator. Lastly, the Stochastic Oscillator can be used to identify potential overbought and oversold conditions in price movements. An overbought condition is generally described as the Stochastic Oscillator being greater than or equal to the 80% level while an oversold condition is generally described as the Stochastic Oscillator being less than or equal to the 20% level. Trades can be generated when the Stochastic Oscillator crosses these levels. A buy signal occurs when the Stochastic Oscillator declines below 20% and then rises above that level and a sell signal occurs when the Stochastic Oscillator rises above 80% and then declines below that level.

For the purpose of our study, we will use this last approach, as buy signal will be generated when both lines rise above the 20% oversold level, and a sell signal will be issued when both lines fall below the 80% over overbought line. For our model purposes, all days which follow a buy signal are referred to as buy days, henceforth, before the sell signal is issued, and all days which follow an issue of the sell signal are referred to as sell days, henceforth, before the buy signal is issued.

3.2.3) Bollinger Bands

Developed by John Bollinger in the beginning of the 1980’s, Bollinger Bands are volatility bands placed above and below a moving average. The volatility to compute those bands is based on the standard deviation, which changes as volatility increases and decreases, making the bands automatically adjust themselves to the market conditions, widening, moving further away from the average, when volatility increases and narrowing, moving closer to the average, when volatility decreases.

In order to use this indicator, we need to have three bands: a *middle band*, an *upper band* and a *lower band*. The middle band is a simple moving average of the asset’s price, which Bollinger defined as a 20 days period SMA. That is the same criteria that will use when computing the middle band in our study. The remaining two outer bands, the upper and the lower, are made using the standard deviation of the price. The look-back period for the standard deviation is the same as for the simple moving average, 20 days in our case. The upper and lower band will be obtained by adding and subtracting, respectively, two times the 20 days standard deviation to the middle band. The formulas for each band can be found below:

Middle Band = 20-day simples moving average (SMA)

$$\textbf{Upper Band} = \textbf{20-day SMA} + (\textbf{20-day } \boldsymbol{\sigma} * 2)$$

$$\textbf{Lower Band} = \textbf{20-days SMA} + (\textbf{20-day } \boldsymbol{\sigma} * 2)$$

There are many different ways of using this indicator in order to produce buy and sell signals. The bands can help identify *W-Bottoms*, which is formed in a downtrend and involves two reaction lows, and can indicate a bullish breakout or *M-Tops*, which are the opposite of the above described bottoms, which can identify a bearish market reaction. It is also possible to *Walk with the Band*, selling when the price touches the upper band, as, arguably, its next most probable move will be to converge to the mean, or buy when it touches the lower band, for the inverse reasons. Buy and sell signs can as well be extracted from the *Bandwidth*, which is another indicator that derives from the original bands. *The Squeeze* is a popular sign that can be tracked by this indicator. This occurs when volatility falls to a very low level, as evidenced by the narrowing bands. A Squeeze and break above the upper band can be seen as bullish, while a Squeeze and break below the lower band can lead to a bearish reaction. *Overbought* and *Oversold* situations can also be identify with the bands, as when the price approaches the upper band an overbought situation can arise, and the opposite for when the price touches the lower band. However, overbought is not necessarily bullish for instance. It takes strength to reach overbought levels and overbought conditions can extend in a strong uptrend.

According to Bollinger (2002), the bands should contain 88-89% of price action, which makes a move outside the bands significant. We can conclude that a move to, or over, the upper band shows strength, while a sharp move to, or below, the lower band shows weakness. The upper band, for instance, is two standard deviations above the 20-period simple moving average. It takes a pretty strong price move to exceed this upper band. Those upper touches can then be seen as trends continuation warnings. That being said, and for the purpose of our study, we will consider a buy signal when the stock price first exceeds the upper band, and a sell sign when it first crosses below the lower band. Thus, we have:

a) *Buy Signal*

P > Upper Band

b) Sell Signal

P < Lower Band

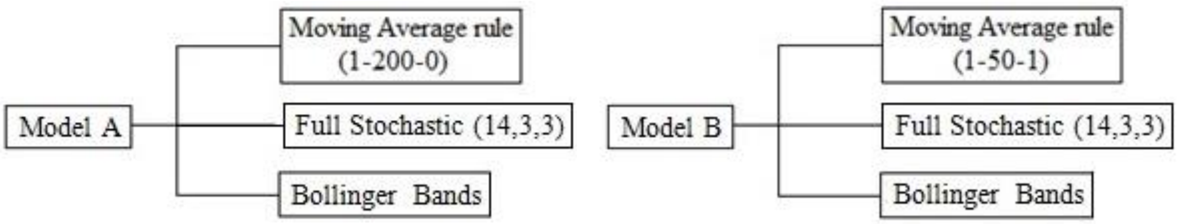
Where *P* is the stock closing price, and the *Upper* and *Lower Bands* are described above.

Just like the other indicators, and for our model purposes, all days which follow a buy signal are referred to as buy days, henceforth, before the sell signal is issued, and all days which follow an issue of the sell signal are referred to as sell days, henceforth, before the buy signal is issued.

3.2.4) Model specifications

The technical trading model that we will use will comprise the three above described rules/indicators. Since we want to do a profitability test, we will need to have moments when the hypothetical investor possesses the assets (stocks), and others when he/she doesn't have them. For that purpose, our model will give us buy signal and sell signals, just like every individual rules, acting as an aggregate. The moments after a buy sign, where the investor will have the asset, will be called *buy periods*, which will end with the following sell signal, when the investor liquidate his/her positions and moves out of the market. Those periods will be named *sell periods*.

We will test two different moving averages rules (the 1-200-0 rule and the 1-50-1 rule), and, since then, we will have two different models, each model with the following trading rules:



We will look for *confirmation*, referring to the comparison of the chosen technical signals and indicators to ensure that most of them are pointing in the same direction and are confirming one another.

Since each model have three different rules, we will give each rule the same weight in the determination of the model's buy and sell signs, which means that, we will only consider a model buy or sell sign when at least two of the individual rules that make the model give us that same sign. If only one rule gives us the sign, we will consider it "whiplash" and won't take it in consideration. It is based on the model's buy and sell signs that we will work upon, and carry the necessary econometric approach.

3.2.5) Transaction Costs effect

In a broader definition, transaction costs can be seen as the costs associated with exchange of goods or services and incurred in overcoming market imperfections. Coase (1988) states that, when dealing with transaction costs, we must keep in mind that those costs are associated with an exchange of rights, and not with the exact good or object that is being transacted. Being so, they play a crucial role in how rights are allocated in an economy. For the purpose of our study, these are expenses incurred when buying or selling securities, and include costs such as brokers' commissions and spreads (the difference between the price the dealer paid for a security and the price the buyer pays). These costs are the payments that banks and brokers receive for their roles in these transactions, and they can vary depending on which market the investor operates, the financial intermediary that he/she chooses or the number of trades per period.

In our study, we will analyze the prices that the main financial intermediaries operating in Portugal charge, and assume that average as our transaction cost per operation (buying or selling of assets). We will assess the effect that the transaction costs have in our research questions, and whether they can, or cannot, erase or decrease our technical model possible profitability.

3.3 Stock characteristics description

In our study, we will analyze the possible impact that four stock characteristics can have on technical analysis profitability, namely the size of the company, the liquidity of the stock, its volatility and the industry where it is inserted. In this section, we will make a brief description of every characteristic.

a) Size

The size of each company and, consequentially, of each stock, will be measured by its market capitalization, with stocks belonging to companies that could be called "Big caps" or "Small caps". The market capitalization is calculated by multiplying the number of a company's shares outstanding by its stock price per share. The definitions of "Big Caps" and "Small Caps" are in permanent change, as companies can pass from "Big" to "Small" Cap in just a matter of years. Despite that, "Big Caps", an abbreviation for "big market capitalization", are considered, as the name itself says, companies with huge market capitalization values, which values stand aside from companies in the same sector or index. They are normally old, well-established companies, and the risk/probability to fail associated with the investment in those companies being very low. On the other hand, "Small Caps", are companies with low values of market capitalization, which can also be newly-IPO companies, which represent a riskier investment, but also profitable opportunities. For the US market, for instance, Russell (2013) defines small-cap as the first 2000 stocks outside the largest 1000.

In the Portuguese Stock Exchange, companies like *Galp Energia*, *EDP – Energias de Portugal* or *Jerónimo Martins* can be considered big-caps, as, on the other hand, companies like *Reditus*, *Copam* or *Inapa* can be seen as small-caps.

b) Liquidity

Liquidity can be defined as the easiness in which an asset can be bought or sold, i.e. the ability to convert an asset to cash quickly. The liquidity of each stock will be measured by its turnover by volume, which is the number of stocks traded in a market during a given period of time, i.e. the amount of shares that change hands from sellers to buyers as a measure of market activity. So, naturally, a stock with higher levels of volume is more liquid than a stock with lower levels of it. Volume is a crucial indicator in technical analysis as it is used to measure the strength of a market move. Blume *et al.*

(1994) conclude that volume plays a role beyond simply being a descriptive parameter of the trading process.

In the Portuguese case, for instance, on the last year of our sample, companies like *BPI*, *BCP* or *Portugal Telecom* are very liquid, contrary to companies like *Corticeira Amorim*, *Impresa* or *Novabase*, which are in the less liquid bottom of the market.

c) Volatility

Volatility, in its simplest way, can be defined as the degree to which prices vary over a certain length of time. It is a statistical measure of the dispersion of returns for a given security (stocks in our case) or market index, and can either be measured by using the standard deviation (of changes in the log of asset prices), or variance between returns from that same security or market index. It is an important measure for quantifying risk: for example, a security with a volatility of 50% is considered having very high risk because it has the potential to increase or decrease up to half its value. Commonly, the higher the volatility, the higher its price variations, and so, the riskier the security.

Other possible measure of stock relative volatility to the market is its *beta*. A beta is a measure of the volatility, or systematic risk, of a security in comparison to the market as a whole. It approximates the overall volatility of a security's returns against the returns of a relevant benchmark (normally, the market where the stock is present is used). For instance, a stock with a beta value of 1.2 has historically moved 120% for every 100% move in the benchmark, based on price level, as, on the other hand, a stock with a beta of 0.7 has historically moved 70% for every 100% move in the underlying index.

For the purpose of our study, we will measure stock volatility based on the standard deviation of its historical daily prices.

d) Industry

In our industry analysis, we will use the same classification made by the Industry Classification Benchmark (ICB). The ICB is an industry classification taxonomy launched by *Dow Jones* and the *FTSE* in 2005 which divides the market into increasingly specific categories, allowing investors to compare industry trends between well-defined subsectors. It uses a system of 10 industries, partitioned into 19 supersectors, which are further divided into 41 sectors, which then contain 114 subsectors. In our study, we will insert our stocks into the 19 *supersectors*, which are: *Oil & Gas*, *Chemicals*, *Basic Resources*, *Construction & Materials*, *Industrial Goods & Services*, *Automobiles & Parts*, *Food & Beverage*, *Personal & Household Goods*, *Health Care*, *Retail*, *Media*, *Travel & Leisure*, *Telecommunications*, *Utilities*, *Banks*, *Insurance*, *Real Estate*, *Financial Services*, and *Technology*. We will also add an *Other* category, in case any of the stocks does not include itself in any of the above mentioned *supersectors*.

After we conclude if the stocks are profitable or nor under technical analysis rules, we will try to find any existing link between a firm´s industry and the profitability of technical analysis trading rules, by seeing if the number of significantly positive stocks are randomly spread across different industries or not.

3.4 Statistical approach

Our first step will be testing the profitability of the model, using conventional statistical tests, traditional *t-tests*. Our model provide us with buy and sell signals, above described, signals that we will use, as well as data like stock returns. In order to obtain a comprehensive answer to the question of technical analysis profitability, the following hypotheses are formulated and will be tested:

1) *The returns are significantly larger/smaller than zero;*

For our model to be revealed profitable, we expect returns on buy periods to be bigger than zero and returns on sell periods to be less than zero. We will compare the mean daily returns earned during buy or sell periods with corresponding t-statistics. The procedure for testing is as stated below.

1.1) *For buy days:*

$$\boldsymbol{H_0}: \overline{\boldsymbol{X_1}} = \boldsymbol{0}$$

$$\boldsymbol{H_1}: \overline{\boldsymbol{X_1}} > 0$$

With the corresponding t-statistics being the following:

$$\boldsymbol{t} = \frac{\overline{\boldsymbol{X_1}}}{\frac{\boldsymbol{s_1}}{\sqrt{\boldsymbol{n_1}}}}$$

Where,

$\overline{\boldsymbol{X_1}}$ is the mean return on buy days;

$\boldsymbol{s_1}$ is the standard error estimated from the buy days sample;

$\boldsymbol{n_1}$ is the number of returns on buy days.

1.2) For sell days:

$$\boldsymbol{H_0}: \overline{\boldsymbol{X_2}} = \boldsymbol{0}$$

$$\boldsymbol{H_1}: \overline{\boldsymbol{X_2}} < 0$$

With the corresponding t-statistics being the following:

$$\boldsymbol{t} = \frac{\overline{\boldsymbol{X_2}}}{\frac{\boldsymbol{s_2}}{\sqrt{\boldsymbol{n_2}}}}$$

Where,

$\overline{\boldsymbol{X_2}}$ is the mean return on sell days;

$\boldsymbol{s_2}$ is the standard error estimated from the sell days sample;

$\boldsymbol{n_2}$ is the number of returns on sell days.

2) The returns on buy and sell days differ appreciably

We will verify the previous results by comparing returns on buy and sell periods. In order for our model to be profitable, both returns should significantly differ. We will compare the mean daily returns earned during buy and sell periods with corresponding t-statistics following two-tailed distribution. Under the null hypothesis, these returns will not differ. The procedure for testing is as stated below.

$$\boldsymbol{H_0}: \overline{\boldsymbol{X_1}} - \overline{\boldsymbol{X_2}} = \mathbf{0}$$

$$\boldsymbol{H_1}: \overline{\boldsymbol{X_1}} - \overline{\boldsymbol{X_2}} \neq \mathbf{0}$$

With the corresponding t-statistics being the following, as used in Brock *et al.* (1992):

$$\boldsymbol{t} = \frac{\overline{\boldsymbol{X_1}} - \overline{\boldsymbol{X_2}}}{\left(\sqrt{\frac{\boldsymbol{s_1^2}}{\boldsymbol{n_1}} + \frac{\boldsymbol{s_2^2}}{\boldsymbol{n_2}}}\right)}$$

3) *The returns on buy days exceed returns on a buy and hold strategy*

Lastly, we will compare returns obtained using our model to a simple "buy-and-hold strategy". We will assess whether the respective returns are equal to the unconditional mean daily returns with corresponding t-statistics. Under the null hypothesis, the returns earned using technical trading rules on buy days do not differ significantly from returns earned according to a "buy-and-hold" strategy. The procedure for testing is also stated below.

$$\boldsymbol{H_0}: \overline{\boldsymbol{X_1}} - \overline{\boldsymbol{X}} = \mathbf{0}$$

$$\boldsymbol{H_1}: \overline{\boldsymbol{X_1}} - \overline{\boldsymbol{X}} \neq \mathbf{0}$$

With the corresponding t-statistics being the following, also as used in Brock *et al.* (1992):

$$\boldsymbol{t} = \frac{\overline{\boldsymbol{X_1}} - \overline{\boldsymbol{X}}}{\left(\sqrt{\frac{\boldsymbol{S}}{\boldsymbol{N}} + \frac{\boldsymbol{s_1^2}}{\boldsymbol{n_1}}}\right)}$$

Where,

$\overline{\boldsymbol{X}}$ is the unconditional mean daily returns;

N is the number of observations;

S is the standard error estimated from the entire sample.

For every hypothesis tested, if we cannot reject the null hypotheses formulated in this section, we cannot find evidence of our model profitability. Considering the size of our sample, and some statistical tests below described, critical values corresponding to a normal distribution will be used instead of those corresponding to a student distribution. The critical values are 1.282, 1.645 and 2.326 (for levels of significance α 10 %, 5 % and 1 %, respectively) and their negative equivalents will be used when needed. For two tailed distribution related to the second hypothesis the values 1.645, 1.96, 2.576 (for levels of significance 10 %, 5 % and 1 %, respectively) will be used. Hence, for a certain α level of significance, if the resulting T is bigger than the critical value, we will reject the null hypothesis.

After assessing the model profitability *per si*, and comparing its results with a "buy-and-hold" strategy, we will compare the size, volatility and liquidity of the stocks which generate positive statistically significant returns to those which do not, in order to see if those characteristics have any effect on the results, which is our main research question. The procedure for these tests will be explained on section 4.5.

4. Empirical Results

In this section, we will present the empirical results of the test statistics presented above. We will divide this section into 5 subsections, as described in the introduction.

4.1 Investor assumptions

To proper conduct our study, we will need to establish some considerations about our hypothetical investor. Here are the main ones:

a) Our investor will be relatively risk averse and will not incur on short-selling techniques. He or she will start a trade after our model produces a buy signal, and will keep the trade open until the model produces a sell sign. After that sign, the investor will liquidate its positions, to re-open them after the model's next buy signal. When the investor isn´t on the market, it will simply keep its funds in liquidity/cash form;

b) Our investor will not be an intraday investor, which means that the enters and the exists of the market will be made at the day's closing price, when our model produces its signs;

c) Since our study will be about the Portuguese Stock Exchange, we will use to open and close our investor's trades a Portuguese based broker;

d) On the last step of our study, we will compare the model´s results with a simple "Buy-and-Hold" strategy. In that strategy, we will assume that our investor buys the assets in the first day of our sample and liquidates its positions on the last one, making no changes in its portfolio, regardless of the price fluctuations in the market;

e) At the end of our eleven year time sample, our investor will exit any open trade, liquidating its positions;

f) Our investor won't set any stop losses or take profit orders. Him or her will simply liquidate its positions or enter a new one once a signal appears;

g) Our investor won't have a risk management and exposure strategy. Whenever the model tells to enter in a trade, him or her will open the position with the full amount of capital, divesting also the full amount when the model produces a sell signal;

h) As mentioned above, we will perform our study with and without transaction costs, in order to assess its effects in our model. To compute the value to use, we analyzed the prices practiced by all brokers acting in Portugal, to get to an average cost per operation for every market order above 10.000€, using the internet as the only negotiation channel. These prices and calculations can be found on Appendix 1. We reached a value of 0,168%, value which we will use.

4.2 Sample descriptive analysis

To start off this section, we will present an analysis of the daily returns of the PSI 20 index, with the main aspects presented in the table below.

	2003-2013	**2003 – July 17 2007**	**July 18 2007 - 2013**
Number of days	2870	1185	1685
Mean	0.00413% (0.000041362)	0.07218% (0.000721885)	-0.04372% (-0.000437226)
Std. Deviation	1.162% (0.011627333)	0.628% (0.006282741)	1.421% (0.014213413)
Skewness	-0.146524803	-0.100478460	-0.049309604
Kurtosis	12.37	5.83	9.27
$\boldsymbol{\rho(1)}$	0.058	0.057	0.055
$\boldsymbol{\rho(2)}$	-0.006	0.035	-0.015
$\boldsymbol{\rho(3)}$	-0.027	0.029	-0.038
$\boldsymbol{\rho(4)}$	0.002	0.058	-0.009
$\boldsymbol{\rho(5)}$	-0.040	-0.038	-0.043
JB Normality Test	10504.66	398.3821	2759.124
Probability	0.00	0.00	0.00

Table 2 - Daily returns are presented for the full PSI 20 sample and for two nonoverlapping subsamples. Daily returns are measured as log differences of the level of the index: $r_t=\ln(x_t/x_{(t-1)})$. $\rho(i)$ is the

estimated autocorrelation at lag i of r_t. ‘JB Normality Test’ stands for the Jarque-Bera Test. Probability is the probability that a Jarque-Bera statistic exceeds (in absolute value) the observed value under the null hypothesis - a small probability value leads to the rejection of the null hypothesis of a normal distribution.

Table 2 contains the summary statistics for daily returns for the complete PSI 20 sample and for two nonoverlapping subsamples, corresponding to the periods between January 1st 2003 and July 17th 2007 and July 18th 2007 and December 31st 2013, having the first sub-period 1185 observations and the second one 1685. Returns are calculated as log differences of the PSI 20 level. Returns are leptokurtic (fat tailed) and negatively skewed for the entire sample and both subsamples. Volatility is larger for the second sample, in which the market was in its bear state. However, the mean daily return is larger foe the first period. Serial correlations are generally small, with a few negative values. For the whole sample and both of the subsamples, we can reject the null hypothesis of a normal distribution, that the Jarque-Bera statistic is distributed as χ^2 with 2 degrees of freedom, proving so that the samples are normally distributed.

As we can see, a simple “Buy-and-Hold” strategy for the whole eleven years sample produced mean daily returns of approximately 0,00414%, which is about 1,08% at an annual rate (the annual average return is calculated by multiplying the daily mean return by 261, which is the average number of trading days in a year). The results, however, are different for the two sub-periods. The first one, that corresponds to the bull market, as we above mentioned, produced daily returns of about 0,0722%, almost 18,84% at an annual rate, as, on the other hand, the second sample, corresponding to the bear market, produce negative daily returns, of about -0,0437%, meaning almost -11,41% at an annual rate.

4.3 Models application results

After looking at the daily returns of the PSI 20 index, which characterize a simple “Buy-and-Hold” strategy, we will analyze the results of our models for the complete eleven year sample and for the two sub-periods, which are present in tables X-Y.

The columns labeled “Buy” and “Sell” present the mean returns obtained during buy and sell periods, respectively: as mentioned on previous sections, a buy period, for example, is defined as the period after a buy signal up to the next sell signal, with the sell period being the other way around. The column labeled “Buy-Sell” presents the difference between these two means. The complete sample results are presented below, on table 3.

Model	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
Model A	1641	1212	0.0912 (0.0003) (0.0032)	-0.1146 (0.0008)	0.545	0.477	0.2058 (1.6E-05)
Model B	1670	1183	0.0963 (0.0004) (0.0019)	-0.1270 (0.0008)	0.549	0.470	0.2233 (3.5E-06)
Average			0.09375	-0.1208			0.21455

Table 3 – Results of the models application: complete sample, 2003-2013. ‘N(Buy)’ and ‘N(Sell)’ are the number of buy and sell days generated by the model. ‘Buy’ and ‘Sell’ are the daily mean returns on the buy and sell periods. ‘Buy > 0’ and ‘Sell > 0’ are the fraction of buy and sell returns greater than zero. Numbers in parenthesis are the p-values, for a confidence level of 95%, testing the difference between the mean buy returns and zero, between the mean sell returns and zero and between buy-sell and zero. The second number in parenthesis in the ‘Buy’ column is the p-value, for a confidence level of 95%, testing the difference between the mean buy returns and the unconditional mean returns. The mean returns are scaled by a factor of 100 for easier interpretation.

For the complete sample, the differences between the mean buy returns and zero, the mean sell returns and zero, the buy – sell and zero and between the mean buy returns and the unconditional mean returns are significantly positive for both models. As we can see, for both models, the mean buy returns are positive, with Model A producing 0,0912% daily returns (about 23,8% at an annual rate), and Model B producing 0,0963% daily returns (approximately 25,1% annually), both models with results way superior to the unconditional mean 1,08% annual rate returns given by a “Buy-and-Hold” strategy, and that can be found characterized on the section above. For both models, sell mean returns are negative, with Model A producing an average daily return of -0,1146% and Model B of -0,1270%. The average return of the models of the buy periods is 24.5% at an annual rate. The “Buy > 0” and “Sell > 0” columns present the fraction of buy and sell returns that are greater than zero. The buy fraction is, for both models, greater than fifty percent, while that for sells is considerably less, being in the region of forty-seven percent. Under the null hypothesis that technical trading rules do not produce useful signals, these fractions should be the same: a binomial test shows that these differences are highly significant and the null of equality can be rejected.

Tables 4 and 5 report our findings for the two sub-periods investigated here.

Model	**N(Buy)**	**N(Sell)**	**Buy**	**Sell**	**Buy > 0**	**Sell > 0**	**Buy-Sell**
Model A	861	307	0.1183 (0.0004) (0.088)	-0.0572 (0.0008)	0.580	0.404	0.1755 (7.5E-05)
Model B	794	374	0.1315 (0.0004) (0.033)	-0.0538 (0.0007)	0.591	0.412	0.1853 (4.0E-06)
Average			0.1249	-0.0555			0.1804

Table 4 - Results of the models application: 1st sample, 2003-July 17 2007. Meanings are the same as in table 3.

Table 4 gives us the results for the first sample, in which a strong bull market occurred, and in which volatility decreased and the mean daily returns increased when compared to the overall sample. We can see that both models give us positive daily mean buy returns, with Model A producing mean daily returns of 0,1183%, about 30,9% at an annual rate, and Model B mean daily returns of 0,1315%, translating into approximately 34,3% annually. Both models, for the first sample, give us results superior to the unconditional mean returns, of approximately 18,84% at an annual rate. However, Model A fails to give statistical significant results when testing the differences between the mean buy returns and the mean unconditional returns, for a confidence level of 95%. That can be explained by the relatively low number of observations of this sample, as we would have significant results if we lowered the confidence level to, for instance, 90% (σ = 10%). All the other differences between means are statistical significant. Sell mean returns are negative for both models, with Model A producing an average daily return of -0.0572 % and Model B of -0.0538%. Also for this first sample, the buy fraction is, for both models, greater than fifty percent, while that for sells is considerably less, being in the region of forty to forty-one percent, with the same conclusions lay above.

Model	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
Model A	780	905	0.0612 (0.0007) (0.035)	-0.1341 (0.0010)	0.508	0.473	0.1953 (3.1E-05)
Model B	876	809	0.0644 (0.0008) (0.026)	-0.1608 (0.0012)	0.511	0.465	0.2252 (0.0014)
Average			0.0628	-0.1475			0.21025

Table 5 - Results of the models application: 2nd sample, July 18 2007-2013. Meanings are the same as in table 3.

Table 5 gives us the results for the second sample, in which a bear market occurred, and in which volatility increase and the mean daily returns decreased when compared to the overall sample. Just like the previous sample, we can see that both models give us positive daily mean buy returns, with Model A producing mean daily returns of 0,0612%, about 16,0% at an annual rate, and Model B mean daily returns of 0.0644%, translating into approximately 16,8% annually. Both models, for the second sample as well, give us results superior to the unconditional mean returns, of approximately -11,41% at an annual rate. Sell mean returns are negative for both models, with Model A producing an average daily return of -0.1341% and Model B of -0.1608%. Also for this second sample, the buy fraction is, for both models, greater than fifty percent, while that for sells is less, being in the region of forty-three to forty-five percent, with the same conclusions described above. For this sample, all the above described statistical tests are statistical significant.

Now that we have analyzed our models results in the PSI 20 index, we will replicate this same procedure for all the individual stocks that constituted our sample, and that can be found in the previous sections. All stocks have proven to have mean buy and sell returns statistically significantly different than zero, as well as buy – sell returns also different from zero. Below, Table 6 synthetizes the main results for each stock, and the results for the test comparing the mean buy returns and the unconditional mean returns are displayed.

Stock	Full Sample			1st Sample			2nd Sample		
	B-a-H	M. A	M. B	B-a-H	M. A	M. B	B-a-H	M. A	M.B
ALTRI [1]	25.0%	42.3% (0.262)	47.5% (0.139)	106.9%	110.1% (0.914)	111.0% (0.893)	-5.1%	18.0% (0.181)	24.8% (0.076)
BCP	-17.1%	18.7% (0.001)	30.1% (0.001)	15.1%	25.4% (0.443)	32.9% (0.181)	-39.8%	14.1% (0.007)	29.0% (0.001)
BPI	-3.9%	19.2% (0.063)	25.0% (0.020)	24.9%	24.7% (0.990)	24.3% (0.964)	-24.1%	15.3% (0.037)	25.6% (0.009)
CIMPOR	-1.7%	14.8% (0.090)	15.8% (0.077)	18.5%	17.4% (0.909)	18.0% (0.962)	-15.9%	13.0% (0.056)	14.2% (0.051)
CIPAN	-15.4%	6.0% (0.602)	-2.8% (0.765)	16.2%	38.3% (0.677)	23.4% (0.893)	-37.7%	-16.4% (0.719)	-20.9% (0.786)
COFINA	-5.8%	21.2% (0.071)	32.3% (0.013)	15.11%	20.7% (0.655)	24.8% (0.440)	-20.5%	21.6% (0.078)	37.5% (0.018)
COMPTA	-25.9%	23.4% (0.071)	8.2% (0.232)	-32.4%	12.9% (0.137)	8.9% (0.204)	-21.3%	30.6% (0.208)	7.7% (0.499)
CORTICEIRA AMORIM	9.2%	25.5% (0.146)	27.8% (0.095)	21.3%	32.2% (0.414)	33.2% (0.360)	0.79%	20.8% (0.225)	24.1% (0.159)
EDP	5.1%	13.2% (0.376)	12.1% (0.443)	22.4%	25.8% (0.779)	25.1% (0.823)	-7.10%	4.5% (0.376)	3.1% (0.435)
F RAMADA [2]	5.5%	25.3% (0.456)	37.5% (0.251)	-	-	-	-	-	-
F.C. PORTO	-19.4%	5.1% (0.196)	12.9% (0.096)	-7.8%	7.8% (0.257)	8.1% (0.256)	-27.6%	3.2% (0.317)	16.3% (0.165)
GALP [3]	9.5%	23.1% (0.406)	32.0% (0.167)	82.0%	84.8% (0.933)	84.8% (0.933)	1.25%	16.7% (0.386)	26.5% (0.153)
GLINTT GLOBAL	-19.1%	23.4% (0.049)	46.8% (0.004)	4.4%	15.2% (0.704)	49.2% (0.139)	-35.7%	29.0% (0.037)	45.1% (0.012)
IBERSOL	5.2%	17.9% (0.191)	26.9% (0.026)	25.9%	26.0% (0.996)	26.9% (0.923)	-9.4%	12.4% (0.140)	26.9% (0.015)
IMPRESA	1.9%	36.6% (0.032)	42.3% (0.014)	27.5%	37.4% (0.461)	35.7% (0.545)	-16.1%	36.0% (0.043)	46.9% (0.017)
INAPA	-21.5%	18.5% (0.012)	26.1% (0.003)	-12.3%	7.0% (0.122)	11.4% (0.049)	-28.1%	26.4% (0.033)	35.8% (0.016)

JERONIMO MARTINS	22.3%	27.2% (0.642)	33.1% (0.333)	26.9%	28.9% (0.880)	35.1% (0.515)	19.0%	26.3% (0.654)	31.5% (0.454)
LISGRAFICA	- 18.3%	6.9% (0.679)	37.3% (0.361)	25.7%	53.4% (0.533)	59.7% (0.449)	- 49.2%	-25.2% (0.809)	21.8% (0.471)
MARTIFER [4]	- 41.7%	1.1% (0.015)	-3.4% (0.026)	-	-	-	-	-	-
MOTA ENGIL	10.1%	27.8% (0.137)	33.4% (0.052)	34.8%	34.0% (0.953)	36.5% (0.900)	-7.4%	23.5% (0.082)	31.2% (0.033)
NOS	0.7%	18.5% (0.085)	21.6% (0.044)	18.9%	21.2% (0.851)	22.3% (0.778)	- 12.1%	16.6% (0.062)	21.1% (0.031)
NOVABASE	-7.3%	12.8% (0.030)	17.6% (0.004)	-3.0%	9.5% (0.198)	11.4% (0.141)	- 10.2%	15.1% (0.075)	21.9% (0.023)
PORTUCEL	8.4%	20.9% (0.151)	22.3% (0.107)	21.9%	24.5% (0.818)	26.2% (0.697)	-1.1%	18.6% (0.119)	19.7% (0.096)
PORTUGAL TELECOM	-5.0%	16.9% (0.025)	12.3% (0.087)	10.1%	16.8% (0.567)	14.2% (0.733)	- 15.6%	16.9% (0.025)	11.1% (0.076)
REDITUS	1.5%	25.4% (0.250)	32.9% (0.144)	37.0%	43.0% (0.781)	47.8% (0.616)	- 23.4%	13.2% (0.252)	22.5% (0.167)
REN [5]	-3.2%	3.4% (0.555)	10.9% (0.201)	-	-	-	-	-	-
SAG GEST	- 12.9%	16.7% (0.039)	29.1% (0.004)	7.6%	16.6% (0.460)	21.1% (0.271)	- 27.2%	16.7% (0.053)	34.7% (0.008)
SDC INV.	-1.5%	35.1% (0.049)	46.1% (0.013)	42.6%	51.8% (0.688)	55.9% (0.560)	- 32.4%	23.6% (0.047)	39.3% (0.012)
SEMAPA	8.2%	26.3% (0.040)	25.1% (0.049)	30.9%	37.8% (0.597)	37.9% (0.584)	-7.7%	18.4% (0.032)	16.2% (0.049)
SONAE CAPITAL [6]	- 24.9%	28.0% (0.045)	43.9% (0.010)	-	-	-	-	-	-
SONAE COM	4.5%	21.4% (0.138)	26.5% (0.052)	24.6%	26.9% (0.888)	33.6% (0.585)	-9.7%	17.5% (0.078)	21.6% (0.042)
SONAE INDUSTRIA	- 18.3%	16.6% (0.009)	24.9% (0.001)	20.0%	33.1% (0.520)	38.1% (0.363)	- 45.2%	5.2% (0.004)	15.8% (0.001)
SONAE	12.8%	30.5% (0.132)	35.3% (0.049)	44.3%	42.6% (0.920)	46.8% (0.884)	-9.3%	22.2% (0.049)	27.4% (0.021)

S.L.B. FUTEBOL [7]	-29.7%	38.3% (0.030)	62.4% (0.005)	-317.4%	0% (0.437)	0% (0.437)	-22.5%	38.9% (0.043)	63.3% (0.007)
SPORTING C.P.	-11.7%	13.4% (0.360)	13.6% (0.359)	-2.4%	13.9% (0.403)	13.1% (0.422)	-18.3%	13.0% (0.483)	13.9% (0.477)
SUMOL + COMPAL	-2.9%	10.0% (0.231)	12.3% (0.163)	5.4%	13.3% (0.567)	17.8% (0.376)	-8.7%	7.8% (0.291)	8.5% (0.272)
TEIXEIRA DUARTE [8]	-4.9%	38.7% (0.254)	55.4% (0.123)	-	-	-	-	-	-
V.A. ATLANTIS [9]	-17.7%	7.4% (0.441)	41.0% (0.084)	-23.8%	4.0% (0.392)	20.2% (0.181)	-13.7%	9.7% (0.637)	54.3% (0.189)

Table 6 - Results of the models application, without having in consideration transaction costs, for the full sample, and for the two nonoverlapping subsamples. 'B-a-H' stands for the 'Buy-and-Hold' returns, 'M. A' for Model A and 'M. B' for Model B. Annual average returns are calculated by multiplying the daily mean return by 261, which is the average number of trading days in a year. Numbers in parenthesis are the p-values, for a confidence level of 95%, testing the difference between the mean buy returns and the unconditional mean returns. **1** – Altri stocks began to be traded on 01/03/2005, having the first sample only 621 observations; **2** – F. Ramada stocks began to be traded on 07/07/2008, making it impossible to divide this stock's returns into the two subsamples; **3** – Galp stocks began to be traded on 24/10/2006, having the first sample only 191 observations; **4** – Martifer stocks began to be traded on 28/06/2007, making it impossible to divide this stock's returns into the two subsamples; **5** – REN stocks began to be traded on 09/07/2007, making it impossible to divide this stock's returns into the two subsamples; **6** – Sonae Capital stocks began to be traded on 28/01/2008, making it impossible to divide this stock's returns into the two subsamples; **7** – SLB stocks began to be traded on 21/05/2007, having the first sample only 25 observations; **8** – Teixeira Duarte stocks only began to be traded on 16/08/2010, making it impossible to divide this stock's returns into the two subsamples; 9 – V.A. Atlantis stocks only began to be traded on 30/04/2003, having the first sample only 1087 observations.

The results produced by both models are remarkable. As we can see in the table above, both models, in the vast majority of cases, produce positive returns and perform better than to a simple 'buy-and-hold' strategy. However, and despite that fact, both models also fail in most cases to produce mean buy returns statistically different than unconditional mean returns, for a confidence level of 95%, fact necessary to prove the model's profitability, which can be explained by the relatively small number of observations, when compared to other studies made in the past, rather than the models themselves failing to produce positive results. To continue our analysis, we will only take in considerations stocks where all the assumptions present in section 3.4 are met, and the models reveal to be statistically significantly profitable.

For the full sample, Model A produce positive returns for all the stocks of our sample, performing statistically better than a ‘buy-and-hold’ strategy in 13 of the 38 tested stocks. The stock where it performed better was *Sport Lisboa e Benfica Futebol*, producing returns of 68% more annually than a ‘buy-and-hold’ strategy (38.3% vs -29.7%). Model B, on the other hand, revealed to be profitable in more stocks, performed statistically better than a ‘buy-and-hold’ strategy in 17 of the 38 tested stocks, failing in just one case to produce positive returns. It also performed better on *Sport Lisboa e Benfica Futebol* stocks, 92.1% more when compared with a ‘buy-and-hold’ strategy (64.4% vs -29.7%).

Analyzing the first sample, the smaller subsample, Model A revealed to be statistically profitable in none of the tested stocks, whereas Model B only revealed to be in one stock, *Inapa*, where it produced returns 23.7% bigger than a ‘buy-and-hold’ strategy (11.4% vs -12.3%).

Lastly, for the second sample, Model A was statistically profitable also in 11 of the 38 considered stocks, performing better on *Glintt Global* stock, 64.7% better than the unconditional mean returns (29.0% vs -35.7%). Model B was statistically profitable in 17 of the 38 considered stocks, performing better on *Sport Lisboa e Benfica Futebol* stock, 85.5% better when compared to a simple ‘buy-and-hold strategy’ (63.3% vs -22.5%).

One thing that is easily visible and that we can straightforwardly conclude just by analyzing the above presented results is that both models perform relatively better when the stock price is falling. Having in consideration the full sample, there are several cases when the application of a ‘buy-and-hold’ produces negative annual results, and the application of our both models leads to positive, and statistically significant, results (stocks like *BCP*, *Novabase* or *Sonae Capital*). This happens, for Model A, on 85% of the stocks where it revealed to be profitable, and, for Model B, on 65% of the stocks where it is statistically profitable. This shows us that the models are very accurate in capturing the upper movements of the stock’s prices, telling the investors to move out of the market when the price is declining. Another aspect that we can denote is that, for the vast majority of the analyzed stocks, Model B performs slightly better when compared to Model A, which can mean that the only thing that separates both models is in fact relevant and significant, and that a 1-50-1 moving average rule, as described in the previous sections, works better than a more typical 1-200-0 rule in capturing the stock price's climbing movements. Analyzing the full sample, this happens in 10 out of 12 stocks where both models are statistically profitable (the exceptions to this point are *Martifer* and *Semapa* stocks, in which Model A performed relatively better).

4.4 Transaction costs effect

We will now replicate the same profitability testes made in the previous section, adding the transaction costs variable. To do that, as also mentioned above, we will add an extra cost of 0,168% to each operation that the investor made, i.e., every time our investor opens a long position, and every time that that same position is closed, the investors will face an additional costs of that value. The tables below presents the results of the application of our models, having in consideration the transaction costs, applying them, in the first place, to the PSI 20 index.

Model	**N(Buy)**	**N(Sell)**	**N.Op**	**Buy**	**Sell**	**Buy > 0**	**Sell > 0**	**Buy-Sell**
Model A	1641	1212	62	0.0817 (0.0004) (0.008)	-0.1146 (0.0008)	0.545	0.477	0.1963 (3.6E-05)
Model B	1670	1183	58	0.0875 (0.0004) (0.005)	-0.1270 (0.0008)	0.549	0.470	0.2145 (7.8E-05)
Average				0.0846	-0.1208			0.2054

Table 7 - Results of the models application, having in consideration the transaction costs: full sample, 2003 – 2013. 'N.Op' is the number of operations that our models produce. Other meanings are the same as in table 3.

Since our investor will not enter in short positions, the transaction costs will not apply to the sell returns, only applying to the buy ones, decreasing them. As we can see, all of our statistical tests are significant, validating our model for the full sample. The introduction of transaction costs did in fact reduced the models profits, with Model A producing mean daily returns for the full sample of 0,0817%, about 21,3% at an annual rate, a decrease of approximately 2,5% at an annual level due to transaction costs. The buy returns were also reduced in Model B, passing from the original 25,1% annually to about 22,8%. Although transaction costs did reduce our models profits, we can see that those reductions did not put in question the overall profitability of the model, and won't affect our main conclusions. On tables 8 and 9, presented below, the models applications with the transaction costs are displayed. We can prove that Model B still produced positive results when comparing them to a 'buy-and-hold' strategy, whether the market is on a bull or bear state. As for Model A, it failed to produce statistically significant results, as the mean buy returns and the unconditional mean returns are not statistically different from each other, for both samples.

Model	**N(Buy)**	**N(Sell)**	**N.Op**	**Buy**	**Sell**	**Buy > 0**	**Sell > 0**	**Buy-Sell**
Model A	861	307	19	0.1121 (0.0004) (0.137)	-0.0572 (0.0008)	0.580	0.404	0.1693 (0.0001)
Model B	794	374	13	0.1270 (0.0004) (0.049)	-0.0538 (0.0007)	0.591	0.412	0.1808 (7.8E-05)
Average				0.1196	-0.0555			0.1751

Table 8 - Results of the models application, having in consideration the transaction costs: 1st sample, 2003 – July 17 2007. 'N.Op' is the number of operations that our models produce. Other meanings are the same as in table 3.

Model	**N(Buy)**	**N(Sell)**	**N.Op**	**Buy**	**Sell**	**Buy > 0**	**Sell > 0**	**Buy-Sell**
Model A	780	905	43	0.0492 (0.0007) (0.056)	-0.1341 (0.0010)	0.508	0.473	0.1833 (0.006)
Model B	876	806	45	0.0530 (0.0006) (0.041)	-0.1608 (0.0012)	0.511	0.465	0.2138 (0.002)
Average				0.0511	-0.1475			0.1986

Table 9 - Results of the models application, having in consideration the transaction costs: 2nd sample, July 18 2007 – 2013. 'N.Op' is the number of operations that our models produce. Other meanings are the same as in table 3.

Just like for the models results without transaction costs, we will replicate this same procedure for all the individual stocks that constituted our sample, and that can be found in the previous sections. Below, table 10 synthetizes the main results for each stock. Just like for the previous analysis, all stocks have proven to have mean buy and sell returns statistically significantly different than zero, as well as buy – sell returns also different from zero.

Stock	**Full Sample**			**1st Sample**			**2nd Sample**		
	B-a-H	M. A	M. B	B-a-H	M. A	M. B	B-a-H	M. A	M.B
ALTRI [1]	25.0%	41.4% (0.283)	46.4% (0.157)	106.9%	109.3% (0.926)	109.6% (0.905)	-5.1%	16.9% (0.197)	23.4% (0.089)
BCP	-17.1%	17.4% (0.002)	28.7% (0.001)	15.1%	24.2% (0.484)	31.9% (0.203)	-39.8%	12.7% (0.009)	27.4% (0.002)
BPI	-3.9%	18.2% (0.072)	24.0% (0.025)	24.9%	23.6% (0.930)	23.2% (0.902)	-24.1%	14.6% (0.040)	24.5% (0.011)
CIMPOR	-1.7%	13.3% (0.119)	14.6% (0.098)	18.5%	16.1% (0.826)	17.2% (0.902)	-15.9%	11.2% (0.070)	12.7% (0.063)
CIPAN	-15.4%	4.8% (0.724)	-4.0% (0.862)	16.2%	35.2% (0.801)	20.7% (0.912)	-37.7%	-19.2% (0.812)	-23.1% (0.897)
COFINA	-5.8%	19.8% (0.084)	28.7% (0.016)	15.11%	19.3% (0.734)	23.4% (0.491)	-20.5%	20.3% (0.086)	36.5% (0.020)
COMPTA	-25.9%	20.1% (0.111)	5.5% (0.323)	-32.4%	9.0% (0.282)	5.9% (0.399)	-21.3%	25.9% (0.401)	3.3% (0.617)
CORTICEIRA AMORIM	9.2%	24.0% (0.183)	26.3% (0.119)	21.3%	30.7% (0.471)	32.1% (0.399)	0.79%	19.3% (0.260)	22.4% (0.187)
EDP	5.1%	12.0% (0.450)	10.7% (0.535)	22.4%	25.1% (0.824)	23.7% (0.894)	-7.1%	2.9% (0.442)	0.01% (0.507)
F RAMADA [2]	5.5%	23.7% (0.490)	35.8% (0.276)	-	-	-	-	-	-
F.C. PORTO	-19.4%	2.9% (0.312)	9.4% (0.201)	-7.8%	5.0% (0.312)	4.9% (0.314)	-27.6%	0.2% (0.424)	12.9% (0.199)
GALP [3]	9.5%	21.7% (0.454)	30.5% (0.194)	82.0%	84.0% (0.952)	84.0% (0.952)	1.25%	15.1% (0.430)	25.0% (0.178)
GLINTT	-	21.6%	44.6%	4.4%	12.7%	45.9%	-	27.6%	43.5%

GLOBAL	19.1%	(0.049)	(0.005)		(0.764)	(0.169)	35.7%	(0.041)	(0.013)
IBERSOL	5.2%	14.8% (0.284)	25.1% (0.049)	25.9%	23.9% (0.899)	24.2% (0.922)	-9.4%	10.9% (0.195)	25.1% (0.041)
IMPRESA	1.9%	35.4% (0.037)	40.9% (0.017)	27.5%	36.2% (0.511)	34.4% (0.600)	- 16.1%	34.9% (0.048)	45.4% (0.019)
INAPA	- 21.5%	17.4% (0.014)	25.0% (0.004)	-12.3%	5.7% (0.144)	10.9% (0.059)	- 28.1%	25.5% (0.040)	34.8% (0.017)
JERONIMO MARTINS	22.3%	26.3% (0.708)	31.5% (0.408)	26.9%	28.1% (0.922)	34.1% (0.572)	19.0%	25.3% (0.708)	29.6% (0.524)
LISGRAFICA	- 18.3%	2.1% (0.799)	30.3% (0.401)	25.7%	47.4% (0.613)	52.9% (0.527)	- 49.2%	-29.1% (0.871)	17.2% (0.579)
MARTIFER [4]	- 41.7%	0.0003% (0.018)	-4.47% (0.030)	-	-	-	-	-	-
MOTA ENGIL	10.1%	26.8% (0.156)	32.3% (0.061)	34.8%	33.1% (0.907)	35.4% (0.951)	-7.4%	22.4% (0.091)	30.2% (0.037)
NOS	0.7%	16.9% (0.109)	20.6% (0.049)	18.9%	19.5% (0.945)	21.4% (0.836)	- 12.1%	15.3% (0.073)	20.1% (0.036)
NOVABASE	-7.3%	11.4% (0.040)	16.4% (0.010)	-3.0%	8.3% (0.233)	10.1% (0.174)	- 10.2%	13.8% (0.089)	21.1% (0.027)
PORTUCEL	8.4%	20.9% (0.186)	21.2% (0.137)	21.9%	24.4% (0.883)	25.2% (0.765)	-1.1%	17.5% (0.140)	18.4% (0.118)
PORTUGAL TELECOM	-5.0%	15.4% (0.037)	11.1% (0.111)	10.1%	15.4% (0.649)	12.8% (0.822)	- 15.6%	15.4% (0.032)	9.9% (0.089)
REDITUS	1.5%	20.9% (0.357)	28.9% (0.191)	37.0%	40.9% (0.829)	45.1% (0.711)	- 23.4%	9.7% (0.327)	14.5% (0.320)
REN [5]	-3.2%	0.02% (0.623)	9.4% (0.249)	-	-	-	-	-	-
SAG GEST	- 12.9%	15.7% (0.046)	27.6% (0.005)	7.6%	15.9% (0.496)	20.1% (0.306)	- 27.2%	15.4% (0.060)	33.1% (0.009)
SDC INV.	-1.5%	34.3% (0.061)	44.6% (0.016)	42.6%	51.1% (0.708)	55.1% (0.581)	- 32.4%	22.6% (0.049)	37.5% (0.014)
SEMAPA	8.2%	25.3% (0.055)	24.2% (0.074)	30.9%	36.8% (0.640)	37.0% (0.630)	-7.7%	17.1% (0.042)	15.2% (0.059)
SONAE	-	27.4%	42.8%	-	-	-	-	-	-

CAPITAL [6]	24.9%	(0.047)	(0.012)						
SONAE COM	4.5%	20.3% (0.164)	25.4% (0.065)	24.6%	25.9% (0.933)	32.7% (0.623)	-9.7%	16.4% (0.091)	20.4% (0.052)
SONAE INDUSTRIA	- 18.3%	12.3% (0.036)	19.8% (0.011)	20.0%	28.8% (0.602)	33.0% (0.451)	- 45.2%	2.1% (0.037)	9.89% (0.014)
SONAE	12.8%	29.3% (0.161)	34.1% (0.049)	44.3%	41.5% (0.870)	45.6% (0.936)	-9.3%	20.6% (0.061)	26.0% (0.027)
S.L.B. FUTEBOL [7]	- 29.7%	35.8% (0.036)	60.0% (0.006)	- 317.4%	0% (0.437)	0% (0.437)	- 22.5%	36.2% (0.046)	61.3% (0.009)
SPORTING C.P.	- 11.7%	11.5% (0.391)	11.9% (0.408)	-2.4%	10.1% (0.483)	10.7% (0.492)	- 18.3%	12.1% (0.523)	11.9% (0.568)
SUMOL + COMPAL	-2.9%	5.9% (0.489)	7.9% (0.398)	5.4%	7.8% (0.624)	13.2% (0.451)	-8.7%	4.1% (0.397)	4.3% (0.379)
TEIXEIRA DUARTE [8]	-4.9%	37.3% (0.268)	54.0% (0.131)	-	-	-	-	-	-
V.A. ATLANTIS [9]	- 17.7%	4.8% (0.601)	32.8% (0.177)	-23.8%	0.1% (0.474)	15.1% (0.284)	- 13.7%	6.8% (0.699)	47.1% (0.227)

Table 10 - Results of the models application, having in consideration transaction costs, for the full sample, and for the two nonoverlapping subsamples. Meanings are the same as in table 6.

Both models, once again, fail in most cases to produce mean buy returns statistically different than unconditional mean returns, for a confidence level of 95%. In this analysis, as well, we will just consider stocks where all the assumptions present in section 3.4 are met, and the models reveal to be statistically significantly profitable.

The overall analysis is quite similar to the one without transaction costs. Model A produced statistically positive results in 11 out of 38 stocks tested for the full sample. Once again, it performed better in *Sport Lisboa e Benfica Futebol* stocks, 65.5% better annually than a 'buy-and-hold' strategy, the same stock as Model B, which produced statistically significant results in 16 out of 38 stocks tested, producing results 89.7% better than the unconditional mean returns.

For the first sample, Model A failed to produce significant statistical results in any of the tested stocks, happening the exact same with Model B.

As for the second sample, Model A was statistically profitable also in 10 of the 38 considered stocks, also performing better on *Glintt Global* stocks, 63.3% annually better than the unconditional mean returns (27.6% vs -35.7%). Model B was statistically profitable in 15 of the 38 considered stocks, performing better on *Sport Lisboa e Benfica Futebol* stocks, 83.8% better when compared to a simple ‘buy-and-hold strategy’ (61.3% vs -22.5%).

The same conclusion regarding the performance of the models in bull or bear markets, and the performance of the models against each other, taken in the previous section, also occurred when taking in consideration transaction costs. We can also conclude that, despite the fact that they reduce the profitability of the models, and make them produce results overall less statistically significant, they doesn’t represent a great burden for the investors, and that they won´t affect our study’s conclusions, and, since that is the case, we will use the returns without transaction costs, when needed, in the next section.

4.5 Characteristics influence tests

We will now test whether the stock’s characteristics, described in section 3.3, have any impact on our model’s profitability, comparing the returns of stocks with different profiles in terms of those characteristics. For this analysis, when needed, we will use the full sample returns, without having in consideration the transaction costs. The values for the market capitalization, needed to differentiate the stocks by their size, and for the turnover by value, needed to separate companies by their liquidity, will be the values of the last year of our sample, 2013, in order to keep our conclusions as relevant and actual as possible. The standard deviation, needed to measure each company volatility, will be the full sample one. As we want to test the effect of this characteristics in the model’s profitability, we will only consider the stock where our models revealed themselves statistically profitable, ignoring the other ones.

In order to reach the conclusions that we want, we will separate the stocks that constitute our sample into two groups, one group with a big amount of a certain characteristic to be tested, and other group with a little amount of that same characteristic, “big caps” and “small caps”, or stocks with great volatility and stocks with little volatility levels, for instance. Each group will be constituted by 3 stocks. We will then test if the mean daily return of both of these groups is equal, or statistically different. If it is statistically different, we will be able to conclude that that characteristic in test has in fact influence in the profitability of our models and in technical analysis in general.

Our hypothesis will be defined as below described:

$$\boldsymbol{H_0}: \overline{\boldsymbol{X_1}} - \overline{\boldsymbol{X_2}} = \mathbf{0}$$

$$\boldsymbol{H_1}: \overline{\boldsymbol{X_1}} - \overline{\boldsymbol{X_2}} \neq \mathbf{0}$$

Where,

$\overline{\boldsymbol{X_1}}$ is the mean daily returns on buy days for the group 1;

$\overline{\boldsymbol{X_2}}$ is the mean daily returns on buy days for the group 2;

And the t-statistic being the following, with the same meanings as described in section 3.4:

$$\boldsymbol{t} = \frac{\overline{\boldsymbol{X_1}} - \overline{\boldsymbol{X_2}}}{\left(\sqrt{\frac{\boldsymbol{s_1^2}}{\boldsymbol{n_1}} + \frac{\boldsymbol{s_2^2}}{\boldsymbol{n_2}}}\right)}$$

We will perform these tests for both models.

4.5.1) Size

The criteria we will use to distinguish the stocks in our samples by their size will be their market capitalization. So, in this case, our $\overline{\boldsymbol{X_1}}$ will be the mean daily returns on buy days for 'Big Cap.' stocks, and $\overline{\boldsymbol{X_2}}$ will be the mean daily returns on buy days for 'Small Cap.' stocks.

a) Model A

According to the used database, the companies with bigger and smaller market capitalization values in which Model A proved to be statistically profitable and that will constitute both our groups are, as follows:

Biggest Market Capitalization Values	Smallest Market Capitalization Values
BANCO COMERCIAL PORTUGUES	GLINTT GLOBAL
PORTUGAL TELECOM	INAPA
SEMAPA	SDC INVESTIMENTOS

Table 11 - Biggest and smallest stocks, in terms of Market Cap., where Model A revealed to be profitable.

Our test results are the following:

		‘Big Cap.’ Stocks	‘Small Cap. Stocks’
Daily mean buy returns		0.00079091	0.000982434
Number of Observations		8559	8559
Freedom Degrees	12994		
T Critical (two tailed)	1.960146568		
P-value	0.440979867		

Table 12 - Results for the size influence test on Model A.

Despite the fact that ‘Small Cap.’ stocks produce much bigger daily returns that the ‘Big Cap.’ ones, the p-value for this test is bigger than 0.05, and we cannot reject $\boldsymbol{H_0}$ with a confidence level of 95%, thus, we cannot prove that the mean daily returns for both groups are statistically different, and, so, for Model A, we can say that the size of the stocks have no influence on its results.

b) Model B

According to the used database, the companies with bigger and smaller market capitalization values in which Model B proved to be statistically profitable and that will constitute both our groups are, as follows:

Biggest Market Capitalization Values	Smallest Market Capitalization Values
BANCO COMERCIAL PORTUGUES	GLINTT GLOBAL
NOS	INAPA
SONAE	COFINA

Table 13 - Biggest and smallest stocks, in terms of Market Cap., where Model B revealed to be profitable.

Our test results are the following:

		'Big Cap.' Stocks	'Small Cap. Stocks'
Daily mean buy returns		0.00111632	0.001343324
Number of Observations		8544	8559
Freedom Degrees	14441		
T Critical (two tailed)	1.960128271		
P-value	0.392761754		

Table 14 - Results for the size influence test on Model B.

Once again, just like for the Model A analysis, 'Small Cap.' stocks produce much bigger daily returns that the 'Big Cap.' ones. However, the p-value for this test is bigger than 0.05, and we cannot reject $\boldsymbol{H_0}$ with a confidence level of 95%, thus, we cannot prove that the mean daily returns for both groups are statistically different, and, so, for Model B, we can say that the size of the stocks have no influence on its results.

4.5.2) Liquidity

The stock's Turnover by Volume will be the criteria used to distinguish the stocks in our samples by their liquidity. So, in this case, our $\overline{\boldsymbol{X_1}}$ will be the mean daily returns on buy days for the most liquid stocks, and $\overline{\boldsymbol{X_2}}$ will be the mean daily returns on buy days for the less liquid stocks.

a) Model A

According to the used database, the companies with higher and lower turnover by volume values in which Model A proved to be statistically profitable and that will constitute both our groups are, as follows:

Most Liquid Stocks	Less Liquid Stocks
BANCO COMERCIAL PORTUGUES	S.L.B. FUTEBOL
PORTUGAL TELECOM	NOVABASE
SONAE INDUSTRIA	IMPRESA

Table 15 - Most liquid, and less liquid stocks, in terms of Turnover by Volume, where Model A revealed to be profitable.

Our test results are the following:

		Most Liquid Stocks	Less Liquid Stocks
Daily mean buy returns		0.000666187	0.001065816
Number of Observations		8559	7417
Freedom Degrees	13092		
T Critical (two tailed)	1.960145201		
P-value	0.04725822		

Table 16 - Results for the liquidity influence test on Model A.

As we can see, less liquid stock produce daily mean returns much higher than the most liquid ones, and the test made can confirm that. As the p-value is smaller than 0.05, we are able to reject $\boldsymbol{H_0}$ with a confidence level of 95%, and we can prove that, for the application of Model A, the liquidity of the stocks has in fact influence on its profitability, as it achieves better results when applied to less liquid stocks.

b) Model B

According to the used database, the companies with higher and lower turnover by volume values in which Model B proved to be statistically profitable and that will constitute both our groups are, as follows:

Most Liquid Stocks	Less Liquid Stocks
BANCO COMERCIAL PORTUGUES	IBERSOL
BANCO BPI	S.L.B. FUTEBOL
NOS	NOVABASE

Table 17 - Most liquid and less liquid stocks, in terms of Turnover by Volume, where Model B revealed to be profitable.

Our test results are the following:

		Most Liquid Stocks	Less Liquid Stocks
Daily mean buy returns		0.00098554	0.001207486
Number of Observations		8559	7416
Freedom Degrees	14491		
T Critical (two tailed)	1.960127705		
P-value	0.173728602		

Table 18 - Results for the liquidity influence test on Model B.

Just like for Model A analysis, the less liquid stocks perform better that the most liquid ones. However, in this case, the p-value of our test is bigger than 0.05, and we cannot reject $\boldsymbol{H_0}$ with a confidence level of 95%, thus, we cannot prove that the mean daily returns for both groups are statistically different, and, so, for Model B, we can say that the liquidity of the stocks have no influence on its results.

4.5.3) Volatility

The stock's Standard Deviation will be the criteria used to distinguish the stocks in our groups by their volatility. So, in this case, our $\overline{\boldsymbol{X_1}}$ will be the mean daily returns on buy days for the most volatile stocks, and $\overline{\boldsymbol{X_2}}$ will be the mean daily returns on buy days for the less volatile stocks.

a) Model A

According to the used database, the companies with higher and lower standard deviation values in which Model A proved to be statistically profitable and that will constitute both our groups are, as follows:

Most Volatile Stocks	**Less Volatile Stocks**
S.L.B. FUTEBOL	SEMAPA
GLINTT GLOBAL	NOVABASE
SONAE CAPITAL	PORTUGAL TELECOM

Table 19 - Most volatile and less volatile stocks, measured by the Standard Deviation, where Model A revealed to be profitable.

Our test results are the following:

		Most Volatile Stocks	**Less Volatile Stocks**
Daily mean buy returns		0.001101102	0.00071508
Number of Observations		6094	8559
Freedom Degrees	7852		
T Critical (two tailed)	1.960266154		
P-value	0.098432935		

Table 20 - Results for the liquidity influence test on Model A.

Analyzing the results above, we can see that the most volatile stocks produce bigger returns than the less volatile ones. Despite that fact, we achieve results that are not statistically significant for a confidence level of 95%, as our p-value is slightly greater than 0.05. However, if we lower that same confidence level to 90%, we get statistically significant results, as our p-value is smaller than 0.1. Thus, we can then say that we get statistically significant results, despite them being weak, proving that the daily mean returns of both groups are different, and that volatility has influence, at least at some scale, in the profitability of Model A.

b) Model B

According to the used database, the companies with higher and lower standard deviation values in which Model B proved to be statistically profitable and that will constitute both our groups are, as follows:

Most Volatile Stocks	**Less Volatile Stocks**
S.L.B. FUTEBOL	SEMAPA
GLINTT GLOBAL	IBERSOL
SONAE CAPITAL	NOVABASE

Table 21 - Most volatile and less volatile stocks, measured by the Standard Deviation, where Model B revealed to be profitable.

Our test results are the following:

		Most Volatile Stocks	**Less Volatile Stocks**
Daily mean buy returns		0.001931684	0.000889861
Number of Observations		6094	8559
Freedom Degrees	7548		
T Critical (two tailed)	1.960278325		
P-value	0.002449419		

Table 22 - Results for the liquidity influence test on Model B.

The results for Model B are quite convincing. As we can see from the table above, the most volatile stocks group has much higher returns than the less volatile group. The p-value of the performed test in way smaller than 0.05, which tells us that we can reject $\boldsymbol{H_0}$, and that the mean daily returns of both groups are statistically different. In that way, we can conclude that, for the application of Model B, volatility has a strong influence on its results, as returns for the most volatile stocks are much bigger.

4.5.4) Industry

To perform the industry analysis, we will try to find a link between a certain industry and the number of stocks in which our models produced statistical significant positive results. In the table 17, below, we can found that data. As said in previous sections, we will resort to the Industry Classification Benchmark (ICB).

	Model A			Model B		
Industry name	No. sig. profitable	No. not sig. profitable	Total	No. sig. profitable	No. not sig. profitable	Total
Oil & Gas	0	1	1	0	1	1
Chemicals	0	0	0	0	0	0
Basic Resources	4	4	8	4	4	8
Construction & Materials	1	2	3	1	2	3
Industrial Goods & Services	1	3	4	1	3	4
Automobiles & Parts	1	0	1	1	0	1
Food & Beverage	0	2	2	1	1	2
Personal & Household Goods	0	1	1	0	1	1
Health Care	0	1	1	0	1	1
Retail	0	2	2	1	1	2
Media	1	1	2	2	0	2
Travel & Leisure	1	0	1	1	0	1
Telecommunications	1	3	4	1	3	4
Utilities	0	2	2	0	2	2
Banks	1	1	2	2	0	2

Insurance	0	0	0	0	0	0
Real Estate	1	0	1	1	0	1
Financial Services	0	0	0	0	0	0
Technology	0	0	0	0	0	0
Other	1	2	3	1	2	3
Total	13	25	38	17	21	38

Table 23 - Differences in statistical significant profitability by industry. All of our sample stocks are classified by their industry and the number of statistically significant positive (at the 5% level) and not statistically significant return stocks is counted for each industry. The industry classifications are those given in the Industry Classification Benchmark (ICB). Total is the total number of companies in our sample.

As can be seen from table above, we can see that there are a few industries where 100% of the returns of the stocks that integrate our sample are statistically profitable, such as the *Travel & Leisure, Real Estate* or *Automobiles & Parts* for both models, and *Banks* or *Media* for Model B. However, the number of statistically significant stocks present in the Portuguese stock exchange is too low for this analysis to be meaningful as the industry classifications are too concentrated. That being said, we can conclude that there is no indication of any industry bias in the results with the numbers of significantly positive stocks being randomly spread across the different industries.

5. Conclusions and future research suggestions

The main objective of this dissertation was answering this question. “Can the popularity of technical trading rules be connected to their profitability on stocks with certain characteristics, like size, liquidity, volatility and industry characteristics?”. In order to answer this question, we constructed two models based on different technical analysis trading rules: moving averages, stochastic indicators and Bollinger bands. We have applied them on individual Portuguese stocks over the period of 2003 to the end of 2013, dividing that period into two different sub-periods. Our stock sample is constituted by 38 stocks, which pass in our criteria of trading activity and timing interest.

First, we’ve tested both models profitability, finding that the first model, named ‘Model A’, revealed to be statistically profitable in 13 of those 38 stocks, whilst the second model, named 'Model B’, produced statistically relevant results in 17 stocks. Both models also produce profitable results when applied to the Portuguese main index, the PSI 20. It was also found that the models work better when the stock’s price is falling, and that, due to the differences in their composition, ‘Model B’ performs overall better than ‘Model A’. It also appears that when the technical trading rules do generate profits, these profits are substantial. We’ve then tested the same models having in consideration transaction costs, finding that, despite them reducing the model positive results, they don’t affect in a major way the models profitability, and technical analysis profitability in a general sense.

Lastly, to answer to our main research question, we’ve tested the stocks in which both models revealed themselves statistically profitable to assess if the chosen characteristics have any influence on the models profitability. We reached the conclusion that the chosen trading rules that made our models are more profitable on illiquid and on the most volatile stocks, but this result is not strong. We haven’t found any link between a firm’s industry and the size of the stock on the profitability of the technical analysis models, reaching conclusions in this matter quite similar to the only study made with this investigation purpose.

This study also puts in question the hypothesis of market efficiency in the Portuguese stock market, corroborating the conclusions of previous mentioned studies, as it proves to be possible to beat the index and a ‘buy-and-hold’ strategy in several stocks.

As future discussion suggestions, it would be enriching to explore other stock particularities, as, for instance, if there is a possibility that some stocks that are not included in market indices - the main focus of previous technical analysis studies - have characteristics that can be profitably captured by technical trading rules. Also, other technical trading rules can be exploited, as well as other statistical techniques could be applied to this same research question, that were never used in a Portuguese stock market study, that will produce stronger and more robust results, such as bootstrapping techniques.

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Appendix

Appendix 1) Transaction costs calculations

Broker	**Transaction cost** *(per operation)*
Banco ActivoBank, SA	0%
Banco BPI, SA	0%
Banco Comercial Português, SA	0,104%
Banco de Investimento Global, SA	0%
Banco LJ Carregosa, SA	0,026%
Banco Popular Portugal, SA	0,125%
Banco Português de Investimento, SA	0,099%
Banco Santander Totta, SA	0,104%
Banif - Banco de Investimento, SA	0%
Banif - Banco Internacional do Funchal, SA	0,318%
Barclays Bank PLC - Sucursal em Portugal	0,083%
BEST - Banco Electrónico de Serviço Total, SA	0%
Caixa - Banco de Investimento, SA	0,099%
Caixa Central de Crédito Agrícola Mútuo, Crl	0,13%
Caixa Económica Montepio Geral	0,208%
Caixa Geral de Depósitos, SA	0,104%
Dif Broker - Sociedade Corretora, SA	0,2%
Fincor - Sociedade Corretora, SA	0,2%
Golden Broker - Sociedade Corretora, SA	0,5%
Montepio Investimento, SA	0,234%
Novo Banco, SA	0,135%
Novo Banco dos Açores, SA	0,135%
Orey Financial - Instituição Financeira de Crédito, SA	0,05%
Average	**0,168%**

Source: *Comissão do Mercado de Valores Mobiliários (CMVM)*