Instituto Superior de Ciências do Trabalho e da Empresa

"Market Efficiency, Nonlinearity and Technical Analysis in the Global Market"

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Abstract

In this thesis we investigate market efficiency from a different perspective. Instead of traditional approach to one market in specific, this time around we study market efficiency from a global perspective. See the global market indices as one single market. We used both nonlinear methods and technical analysis in order to accomplish our purpose. We used BDS to test for nonlinearity in the return series, as expected the results conformed with the general view, which is market returns exhibit nonlinear dependence. We trace the cause of the dependence as a result of the ARCH type process. We also used technical trading strategy to test whether profit can be made through trading in stock indices around the world. We investigate the simple moving averages, weighted moving averages and exponential moving averages with different allocation of resources, we found all techniques to be profitable when 1% and 2% commission are considered. For the 50 day simple moving average, the average daily return is 0,0009%, compared with the -0,669% of the buy and hold strategy. These results were also confirmed using bootstrap methodology in which we considered the random walk model as return generating process. These rules are profitable after accounting for commission fees.

JEL classification: G11; G14

Keywords: World market indices; Market Efficiency; Nonlinearity; BDS; Technical analysis; Bootstrap

Resumo

Nesta dissertação analisou-se a eficiência dos mercados numa perspectiva diferente. Em vez da abordagem tradicional a um mercado específico, estudou-se a eficiência de uma forma global. Considerou-se que os índices globais dos mercados formavam um mercado único integrado. Utilizaram-se simultaneamente métodos não lineares e a análise técnica para testar a eficiência do mercado global. Utilizou-se a BDS para testar a não linearidade na série de rendibilidades dos índices, tal como esperado, os resultados confirmaram os estudos anteriores, ou seja, os mercados têm uma dependência não linear. Esta dependência resultará de um processo de tipo ARCH. Utilizaram-se regras de "*trading*" baseadas na análise técnica para testar se é possível obter uma rendibilidade anómala com os referidos índices de acções. Consideraram-se médias móveis simples, ponderadas e exponenciais, ensaiando várias afectações diferentes de recursos (ponderação igual e proporcional), detectou-se que todas as estratégias eram rentáveis mesmo depois de considerar comissões de 1% e até de 2%. Para a média móvel simples de 50 dias, a rendibilidade media diária é de 0,0009%, comparável com -0,669% para a estratégia "*buy and hold*". Estes resultados também foram confirmados através da metodologia de "*bootstrap*", em que se considerou o modelo "*random walk*" como um processo gerador das rendibilidades. Estas estratégias são rentáveis mesmo depois de consideradas as comissões.

JEL classification: G11; G14

Keywords: Indices bolsistas; Efficiência dos Mercados; Não linearidade; BDS; Análise técnica; Bootstrap

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0 Introduction

Market efficiency, which is the answer to the question if prices “fully reflect” the available information, has been the concern of some many distinguished researchers over time and results have been somewhat in favour of efficiency. Although of late there have been some challenging results against the efficient market hypothesis. In all, for most developed countries market efficiency has been upheld, whilst for the developing countries there have been some mixed results. Apart from the econometric studies used to study market efficiency, technical analysis, concerned with the prediction of future price movements based on past prices, has been used to test for efficiency. Earlier technical analysis studies, such as the studies by Alexander (1961), Fama and Blume (1966) and Jensen and Bennington (1970) found technical analysis to be profitable when no commission is taken to account. After which they become unprofitable due to the large amount of transaction required. The basic idea is that under market efficiency theory technical analysis is a useless activity, which is to say it should not be profitable. And all these studies supported this idea. Of late, however, some studies such as the Brock et al. (1992) and Bessembinder et. al (1995) showed that the idea that held technical analysis as a waste of time may be too premature. As they showed technical analysis can be profitable, even after accounting for commission.

Earlier studies carried out on price independence had taken, until recently, more or less for granted that movements in stock market prices are stochastic in nature, if not actually random walk. And it seems unlikely that a pattern in stock market returns could be explained by a deterministic process, given the assumption that price movement in stock prices is due to the flow of news. However, nowadays, there is a broad agreement that nonlinear structures exist in financial series.

Uncovering this phenomenon his due to the effort on the part of researchers, which upon observing some departure from efficiency Fama (1991) and Lo and Mackinlay (1989) and others, tried to find plausible explanations for the phenomenon and these actions led to the creation of a set of tests capable of detecting nonlinear patterns in time series data.

It became clear that many low dimension deterministic processes outputs are similar to white noise's. This implies that one may be led to infer on the assumption of random walks when the process is in fact not a random walk.

In this thesis we propose to study market efficiency from a different perspective. Contrary to previous studies on market efficiency that focused on particular markets or countries, this time we propose to study market efficiency in a global perspective, seeing the entire market indices as a single market. With that aim in mind we selected 50 stock market indices across the global market.

In order to pursue our goal we combined nonlinear studies and technical analysis. We used BDS to test for nonlinearity on the series of returns, instead of the traditional linear models that upheld market efficiency whenever in the presence of zero correlation. For technical analysis we constructed a trading simulation model that combines the size and indices selection as a way to construct a high performance portfolio. To test whether the idea held by professional economists is true that markets are efficient and technical analysis is a waste of time.

In sum, we used non linear models to test for non linear dependence. The result of BDS test gave us indication that all market indices exhibited nonlinear dependence, and that this dependence is transmitted through variance. This fact gave us hope that technical trading strategy might be profitable. The question is whether a naïve approach to technical analysis such as using simple, weighted and exponential moving averages to select the indices and decide when to buy/sell an index can be profitable as well.

We tested the simulation with no commission, 1% and 2% commission fees. For the benchmark, that is for the buy and hold strategy we considered the MCSI Global market index. The result for the buy and hold strategy is -0,669% daily average return. The result for the technical trading rule, 50 days simple moving average, portfolio size 10 and 1%, is 0,0009% daily average return, which is significantly different from buy and hold strategy. These results are robust to commission fees. Contrary to the held belief on technical analysis, this result is economically and statistically significant, and all techniques tested are profitable and statistically significant. The reason for predictability can be traced back to ARCH effect identified by Enlge's LM test.

In addition to standard t-test statistics used, to evaluate the profitability of technical trading strategy, we used bootstrap methodology as suggested by Brock et al.(1992). So as to determine whether the technical trading rule captures the stochastic process underlying the portfolio returns. The bootstrap result conformed with the result of the trading simulation's result.

The remaining chapters are organised as follows: Chapter one describes the concept of fair game, martingale and random walk model and reviews the literature on random walk and marketing efficiency through the 20th century. Chapter two discusses the concept of market efficiency and its evolution, the implication of the concept of market efficiency for investment policy and the tests used to study market efficiency and the results of those studies. Chapter three, discusses the market anomalies, the numbers of anomalies documented are so large that the focus will be directed only to those more robust and common throughout other markets. Chapter fourth describes the methodology employed to test global market efficiency, the nonlinearity test used and the state of the nonlinearity in the financial literature and the model built to simulate transactions. And finally, in Chapter five we present the conclusions to the entire thesis.

Chapter 1

1 Random Walk and Martingale an Introduction

Random walk is one of the most fascinating, challenging and at the same time the most controversial subjects in the world of finance. This can easily be proved by the fact that so many researchers have devoted their time and skill trying to solve this *puzzle*. Like many words in economics, *random walk* was borrowed from physics. Meaning "If the drunk can be expected to stagger in a totally unpredictable and random fashion, he is likely to end up closer to where he had been left than any other point[1]". For the stock market the meaning is basically the same, which is, you cannot predict tomorrow prices based on yesterday prices. The best forecast for tomorrow's price is today's price, since the price itself is as likely to go up as it is likely to fall down. The main idea is that stock market prices cannot be predicted by simply looking at past prices. This line of reasoning allows us to believe that prices are a *fair game*.

1.1 The Martingale Model

In the 16th century, an Italian mathematician conveyed the basic meaning of *fair game* in the following phrase: "the most fundamental principle of all in gambling is simply equal conditions, e.g., of bystanders, of money, of situations, of dice box, and of dice itself. To the extent to which you depart from that equality, if it is in your opponent's favour, you are a fool, and if in your own, you are unjust"[2]. He managed to convey in this definition the basic assumption of "fair game", which is neither in your favour or your opponent's and this is the concept deeply rooted in the Martingale Model. This is shown in the formula below:

$E\ [P_{t+1}|P_t, P_{t-1},\ldots]=Pt$, (1) or equivalently,

$E\ [P_{t+1}-P_t|P_t, P_{t-1},\ldots]=0$ (2).

[1] Karl Pearson *in* Dimson and Mussavian(1998)
[2] Girolamo Cardano *in* the book of Liber de Ludo

This means that, if P_t follows a stochastic process, then the best estimate of tomorrow's price, based on today's information, is today's price (see 1). Or alternately, a game is fair if the gain from estimating tomorrow's price, based on today's information, is zero (see 2), hence the price is as likely to rise as it is to fall. Implying the ineffectiveness of all linear forecasting rules for future price changes based on historical prices alones. In other words, if investors can use any information available today to predict future price, the Martingale Model would be violated.

The Martingale hypothesis was once considered to be a necessary condition for the Efficient Market Hypothesis (EMH). However, as pointed out by Leroy (1973) and Lucas (1978), the forecastability of prices does not imply market inefficiency, nor inefficiency implies forecastability.

1.2 The Random Walk Model

A process is called Random Walk if it cumulatively encompasses the Martingale conditions in addition to the independency of high conditional moments (i.e., variance, skewness, and kurtosis). Random Walk means that future price level is no more predictable than the path of accumulated random numbers. Price change from past period (t-1) is independent of price change in the next period (t): the series of price changes has no memory. In other words, past price cannot be used to predict future prices. This means that technical and fundamental analysis are of no value to professional investors.

Campbell, Lo and Mackinlay (1997) propose differentiation of the types of random walks. According to them there are three types of random walks, we are in the presence of:

1.2.1 Random walk 1: independent identically distributed (IID) increments

$P_t = \mu + P_{t-1} + \varepsilon_t$, $\varepsilon_t \sim IID(0, \sigma^2)$ (3),

where μ is the expected price change or drift and $IID(0, \sigma^2)$ denotes that ε_t is independently and identically distributed with mean zero and variance σ^2. The independence of increments (ε_t) implies that the random walk is also a *fair game*, but in much stronger sense than the martingale model: it implies that the increments are uncorrelated and also that any nonlinear increments of the functions are uncorrelated.

$E[P_t|P_0]= P_0+\mu_t$ (4)

$Var[P_t|P_0]= \sigma^2_t$ (5)

1.2.2 Random walk 2: Independent increments

The difference from random walk one to random walk two lies in relaxing the assumption of identical distribution of returns. The argument supporting this view stems from the fact that over time the return probability changes. Price changes, though uncorrelated, tend not to be independent over time but instead to have clusters of volatility. It is a more realistic approach to financial markets than random walk one.

1.2.3 Random walk 3: Uncorrelated increment

Random walk three is a more general concept than the previous two. It loosens both the assumption of independency and identically distributed returns.

1.3 Literature Review on Random Walk and Market Efficiency

It is difficult to argue against the idea of random walk, for it bears one of the most important assumptions of modern finance, the idea of fair game. The underlying concept is that, regardless of the level of one's own knowledge of the stock market, one can perform as well as any professional stock market trader, in average. In other words, the best strategy in the stock market is the buy and hold. Buy a stock market index and you are certain to perform as well as or better than any other professional investor and with a plus, you have not spent a huge amount of resource on acquiring information that is useless, because you cannot profit from it. The superior performance of some portfolio manager or any broker is seen as mere luck[3], something that cannot be repeated on a regular basis. Which is to say, no one can beat the market every time, as there is no information in the stock market that gives indication on the direction of the price movement, thus allowing professional investors to outperform the market. Technical analysis is, in sum, a waste of time.

This controversy between market professionals and academics has been going on since the beginning of the stock markets and is still going today even though nowadays, with the new econometrics tools, some light has been shed on the subject, concerning predictability of stock market prices and market efficiency.

There were, back then, two fields of battle clearly established. On the one side the supporters of random theories, mostly economists and academics, and on the other side professional investors and stock market traders which claim that stock prices are predictable. The points of view of one and the other have softened since then and both were forced to admit, to a certain extent, that they were both correct/wrong.

However, all through the late 19th century and the first half of the 20th century, it was not so. Defending either view point would be considered heresy by the other *side*, be it random walks supporters or stock market analysts[4]. Any study presented in support of random walks would be followed by another in support of price trend. On both sides of the battle there were fierce believers. There were, however, in all those studies on the predictability of stock market and market efficiency, some common threads. In none of the studies was there clear rejection of either random walk or price trend in its entirety[5]. There was always something that could not be pinpointed and which was consequently dismissed as irrelevant by one or the other as data anomaly[6]. But, alas, the true lays exactly in these small, ignored details. Many seriously imperfect assumptions were taken from handicapped studies or ignored data.

[3] See Cowles (1933),
[4] Cootner(1962)
[5] Kendall(1955), Osborne(1959), Fama(1970)
[6] Kendal(1953)

Clearly, there were some misunderstandings on the meaning of random walk and stock market predictability, for both, academics and market professionals alike. To the first group it means that the market is not efficient, however, as noted by Lo and Mackinlay[7] citing Leroy's (1973) and Lucas (1978) study, predictability of stock market does not necessarily mean that markets are inefficient. It means simply that prices do adjust to new information. Fama (1970, 1976), also made clear that the assumption of constant equilibrium expected returns over time is not a part of efficient market hypothesis. This is to say that random walk rejection does not imply market inefficiency.

The earlier studies on random walks were concerned with the predictability of stock price movements. It should be added that researches on random walks were not confined to stock market alone or stock market indices or to the US market to that effect. Other markets were also examined, foreign exchange, interest rate[8], commodity market, bond market[9] and future market[10]. Academics in other countries also devoted their time and talent to study the phenomenon in their own markets, with the purpose of determining whether the results in the US market could be replicated in the domestic market; they tested both the predictability and market efficiency[11] as well.

Had it not been for Cootner(1964), Bachelier's (1990) pioneer work on Random Walk theory would have been restricted to a few scholars. Bachelier was the first to derive the random walk theory based on the assumption of zero expectation. In his doctorate's thesis he compared the statistical distribution expected of random theory with the observed distributions of price changes of certain government securities. He found correspondence between what could be expected theoretically with what was observed. Hence, concluded "…tomorrow's price in a particular series cannot be assessed based on yesterday's price".

[7] Non a Random Down Walt Street, also Black (1971)
[8] Fama and Schwert (1977), "Short Term Interest Rates"
[9] Keim and Stambaugh (1986), "Spreads between long and short-term interest rates"
[10] A. A.Larsen, Random Walk and Forward Exchange Rates A Spectral Analysis, random walk and price trends the live cattle futures market, fx
[11] Kendall (1953)

While Bacheliers's thesis was concerned with random walks and price independency, Cowles[12] concern was to identify whether there is an organisation or individual whose forecast ability provided superior investment on the equity market or predicted the future movement of stock market. To Cowles (1933) the question was: Can anyone beat the market? He was testing what is known today as "strong form efficiency" – this wording would become a jargon years later, after Fama's (1966) seminal work on market efficiency. This is a subject to be developed in more detail throughout this thesis, but for now let us say the on the issue of forecasting individual stock price Cowles found that, in general, about 12 out of 36 were successful, thus concluding that these successes were due to pure luck.

On the issue of predictions provided by professional practitioners, he found them inconclusive in some cases; in others practitioners failed to forecast the movement of the stock market. Their performance was 4% bellow the performance by pure chance. The conclusion is obvious, better result would be achieved through random process of stock selection, according to Cowles.

Not satisfied with the previous result, Cowles[13] , this time, tries to extend its research to determine to what extent stock markets are predictable. This would be a test of weak form efficiency, today. The main purpose was to determine the statistical nature of the so called "structure". As a result a technique of ratio of sequence over reversals was used in the hope of revealing the "hidden" structure. According to the authors, "in a truly random series a sequences/reversals would equal ½, the same probability as tossing a fair coin". Their study produced results supporting the price trend theory, there were excess of sequences over reversals in stock market, more than would be expected if the prices follow a random walks process. A sequence is when a rise follows a rise or a decline is followed by a decline, and reversals are when a rise is followed by a decline or a decline followed by a rise. Evidence of "momentum" or "structure" as defined by Cowles et al was uncovered. They also found that stocks that had advanced in one month/year tend to show strength in the following month/year. They try to explain this phenomenon through the impact of the business cycle on behaviour of the stock market[14]. In this situation the best strategy, according to the authors, "would be to swim with the tide". This finding seems to contradict the previous study by Cowles (1933) where he finds no

[12] Cowles (1933)
[13] Cowles and Jones (1937)
[14] This is the concept of event studies

profit for professional speculator. The question then is: is this profit large enough to accommodate for the fees and brokerage costs? Are profits statistically significant? These questions are recurrent whenever simulations of transactions are being examined. The same question will be asked about the results of this thesis.

Kendall and Hill (1953)[15] also delved into the research on weak form efficiency. For them the main question was: How good is the best estimate we can make of next weeks' price if we know this weeks' change and the past weeks changes? They studied the serial correlation of the first difference and found that there were no correlation between today's price and tomorrow's. According to them "… the knowledge of past price yields no substantial information about future price change". They found correlation close to zero in almost all the series and concluded that the "… data behave like a wandering series", being difficult to distinguish statistically between a wandering series and one with a small systematic element. Not only have they argued that it is impossible to predict stock market movements unless with some *extraneous information*, but also that there is no correlation between various stocks that would give any predictive power. Cootner (1962) points out firstly that Kendall and Hill tried to develop a model that would fit the data and not the other way around. Secondly, they ignored the one exception, cotton series, which was dismissed as data anomaly and considered irrelevant for the purpose of study. However, it seems that the serial correlations observed in this series were due to frequency of the data. Contrary to the other series, which referred to data from a specific day, say, Friday's closing price, the cotton series was an average of four or five week observations. The main characteristics of these types of series are serial correlation of 1st order[16]. Finally, limitation techniques may explain why they did not test for increasing variance to test for departure from normality.

In what concerns to the zero correlation, Cootner (1962) argues that this may be due to the combination of negative reactions phenomena on the one side and positive contributions of trends on the other side, thus achieving the zero correlation.

[15] M.Kendall and Bradford Hill(1953)
[16] Autocorrelation induced into returns series as result of thin trading

Roberts (1959), basing on the earlier researches by Working (1934) who had also suggested that stock prices series were random, and Kendall et al. (1953) showed that the series generated by a series of random numbers was indistinguishable from the US stock prices. Whilst Robert's targets were market professionals Osborne's (1959)[17] were physicists from US Naval Research Laboratory. Osborne worked with a series of price change rather than serial correlation like Kendall. He found that changes in the log of prices constitute an "ensemble that appears to be normally distributed"[18]. Osborne's concerned was the statistical distribution of logarithms of price changes, not trend in stock prices. He gave two major contributions to modern financial theory: first he provided background for random walks, and then the use of a logarithm of price change to test for normality[19]. Critics sustain that Osborne wanted to understand which model generated the data, so he constructed a model that fitted the data being observed. The data, still, gives the idea of fairness "…fair meeting ground between buyers and sellers".

There are two major differences between Osborne's studies and Bachelier's, the use logarithms of price change, instead of arithmetic, and the idea that price change independency stems from the investors' action in analysing transactions to transactions, independently. Both Osborne and Bachelier's work bear the idea of normally distributed returns (finite variance), however Mandelbrot (1963) challenged this assumption by showing that there is evidence of high tail distribution without finite variance. In addition he cast some serious doubt on the studies of return independency based on serial correlations[20].

If price were truly random, there would be a major challenge to stock market professional to outperform the market. However, Alexander (1961) believed there were trends in stock markets and the main issue was how to uncover these trends and use them in to our advantage. The way to do this, according to him, was through filter rules (see point 2.4.3 for more detail). The reasoning behind this idea is as follows: if the processes were generated by a random walk process the

[17] Brownian Motion in the stock market
[18] For further discussion on normality assumption under random walks, please see Mandelbrot(1963) and Fama (1966). According to these authors the best distribution for the return series is not a Gaussian type process, but rather a Stable Paretian -type process. Hsieh (1989) suggest a different distribution
[19] for further discussion on the benefits of using Log prices, please see Campbel, Lo and Mackinlay's The Econometrics of Financial Markets"
[20] Fama (1970) also supports the findings by Mandelbrot in that non-normal distributions are better descriptions of daily returns than normal Gaussian distribution.

expected profit should be zero or to vary from zero profits, both positively and negatively, in a random manner. It would be impossible to establish any strategy that would yield profit greater than expected from a buy and hold strategy. Alexander (1961) found his filter rule profitable even after accounting for commissions. And although, he recognises that speculative price changes appear to follow random walk over time, he also admits that once initiated price changes tend to persist over time. What was mentioned as structure by Cowles and Jones (1937) seems to have been confirmed by Alexander. There is momentum in stock market prices. For Alexander "…an average which over a large number of observations follows a pattern consistent to permit a rule that would theoretically make money is not following an equal probability of random walks, in the normal sense".

One of the many critics[21] of Alexander's work argues that: commissions set for transactions are considered too low, the use of simple arithmetic mean instead of logarithm averages, and the actions of investors that could affect the markets (thin trading-market microstructure) in the sense that the buy and sell price would never be the reported. And finally the bias generated from using closing prices instead of the highs and lows. A buy or sell was assumed more favourably then the closing price which signalled the transaction was to take place. Against critics Alexander argues that the data was used for argumentation purposes, not trading.

In his new study Alexander (1964), after correcting for the biases in the previous study, found all his filters to be profitable if no commissions are considered. Some filters reported to be profitable on the first study were not so in the second one, once they had been corrected for the biases introduced in the previous study. Nevertheless, many others filters were profitable, though the gains were relatively small. The apparent profitability is said to be a direct consequence of upward trend in prices and strategy used for simulating transactions (confirmation days will frequently be days of large price change, and consequently of large overshoot). It remains to be proven whether these profits are a result of a random walk process. The 1% filter rules were the

[21] Fama (1965) and Fama and Blume (1966) presented a detailed empirical analysis of filter rules and concluded that such rules do not outperform the buy and hold strategy. In the absence of trading costs, very small filters (1% in Alexander [1964] and between 0,5% and 1,5% in Fama and Blume[1966]) do generate superior performance. These results are consistent with persistent or positive very short term price movements, consequence of serial correlation in the daily price. Small filters are transaction intensive, thus the huge number of transaction generated. As a result, they are very sensitive to transaction costs, as shown by Fama and Blume (1966) even a 0,1% transaction costs is sufficient to eliminate the entire profits.

most profitable of all. In this case the amount of transaction required, due to small filter used, eliminated all the profits, after accounting for commission. Apart from the commission issue there is another issue that as to due with the risk adjustment in what regards to this type of simulation. The criteria tend to pick stocks that are riskier than average. Meaning that after accounting for risk the result may not be as attractive as it was supposed to be. It should be pointed out that a buy and hold strategy would, always, be profitable as long as we are in the upward market trend. Thus, caution should be used in comparing filter rules with the buy and hold strategy.

Alexander came to the conclusion that trends *per se* do not explain the success of the filter rules. He studied the trended prices, though some were unprofitable and in general he found them to be more profitable. Thus, he concluded that data on S&P500 industrial is inconsistent with a process of random walk with drift. But he also conceded that the period of 1928-40 may have played an important role (economic crisis and Second World War)[22].

The issues of independency of prices series have been the main concern for researcher and market professionals, and its degree varies accordingly. The minimum acceptable depends on whether we are referring to market professional or economists. For the latter, the main concern is whether the data is an adequate description of the reality, whilst for the former the main concern is whether past price can be used to obtain abnormal gains. For instance, a perfectly negative serial correlation may be of great importance to academics; however, for the investor it is only important if he/she can use this information to achieve abnormal returns after accounting for transaction costs.

Stock prices is an accumulation of randomly generated noises[23], meaning the effect or actions of investors on given securities, not a result of any political or economic situation. This is a view not shared by most random walk theorists. Some people believe investors are motivated by psychological factors, others by the result of a company evaluation. These investors believe every security has an “intrinsic value”, true value. This is the equilibrium price that will determine their

[22] Perhaps event study might shed some light on this issue.
[23] For more detail on noise trading, see Fisher Black (1986)

action. And whenever there is disagreement or uncertainty on the part of investors about the intrinsic value there is “noise trading”. Disagreement among investors about given information does not imply inefficiency, unless there are investors who systematically make better use of the available information. The *true* value changes over time due to market, political and economic situation that might impact on a company’s future prospects. For Black (1986), sometimes investors trade on what they perceive as information, when in reality they are trading on noise. Although this trading is important to provide market liquidity it can also generate market bubbles[24]. Market bubbles is a phenomenon where noise traders herd[25], it produces dependence in price series as the accumulation of the same type of noise causes the price level to run well above or bellow the “intrinsic value”. To Fama and French (1988a) this is not evidence of market anomaly, “…temporary swings do not necessarily mean rational bubbles…” rather it is a result of a combination of positive expected returns and temporarily high expected returns.

Once independency is attained, whatever the process, chart reading and stock market analysis are no longer profitable activities. However, Fama (1970) argues that there is still room for superior intrinsic value analyst, as there is always new information that changes the intrinsic value. If the information generating process is not independent then successive price change will exhibit dependency. Profit can be made as long as one can predict and assess the new information and act upon it.

Fama (1965) believes sophisticated traders may prevent certain market anomalies, such as bubbles, from happening. The assumption underlying this thought is that these traders recognise the true value of the stock price and in this situation they act in order to maximize their profits. In doing so, not only they ensure the independence of successive price change, but also profit in the process. It should be pointed out, however, that the sophisticated investor has no guarantee that his price assessment is the correct and as a result their actions are constrained. Their actions are also constrained by market frictions (commissions paid for transactions, etc.), thus diminishing their abilities to ensure price change independencies. Whenever there is price dependency there is opportunity for profit making. There is another aspect to this reasoning, that deserves our

[24] For more detail see Kenneth D. West (1988), “Bubbles, Fads and Stock Price Volatility Tests: A Partial Evaluation”; see Jeremy J. Sigel (2003) for a more detailed definition
[25] On investor herding see, Nofsinger,and Sias (1999), Ivo Welch(1999), Hershleifer and Teoh (2003)

attention and this is that the irrational traders sometimes take the upper hand, contrary to common belief that irrational traders loose money. Bradford and Delong (1988) assert that in a risk-averse world of investors the average rewards to risk takers exceed those of risk avoiders and the law of large numbers implies that risk takers as a whole do better than risk averters. Thus, irrationality may, actually, be rewarded in the aggregate.

Lo and Mackinlay (1988) decided to revisit the random walk theory with the firm belief that previous studies conducted by so many remarkable researchers supported this theory because they lacked the statistics robustness that would detect a small but important departure from randomness. To pursue their purpose they developed a test called variance ratio test (see 2.4.4 for more detail). The idea behind this logic lays on the fact that the random walk model's assumption of incremental variance is a linear function of time, which is to say that $r_t + r_{t-1}$ is twice the variance of r_t. Or in other words, in a random walk model, the variance of the returns is proportional to the time elapsed. They applied the test to the US market with the purpose of testing price dependence. The idea is to capture the mean reversion in data. A system is mean reverting if after successive upward change it is more likely to move downwards in the next observation than to continue upward, and vice versa. Lo and Mackinlay rejected the random walk model for the US market. They found weekly and monthly stock returns had positive autocorrelation coefficient contradicting the almost zero autocorrelation reported in early efficient markets literature and the prediction of approximately zero autocorrelation from mean reverting models.

Chapter 2

2 Market Efficiency

Following all these studies it became apparent that stock market prices are predictable to a certain degree. What seemed to be a data anomaly was in fact the answer to the question of the predictability of stock markets.

The question posed then changed slightly, from market predictability to profitability. Is the predictability of stock market prices economically significant, that is, profitable? Can professional investors beat the market after accounting for commissions (market frictions)? These are questions that interest both academics and professional investors alike. For academics it is an interesting question because it tests whether the markets are efficient in what concerns the pricing of securities. For professional investors, the answer to this question may allow them to devise strategies in order to take advantage of the temporary market inefficiency to make profit, and at the same time drive prices to their *true* value.

As mentioned earlier, the reason for so many studies on random walk is because not only were there misunderstandings on the meaning of stock market predictability and random walk, but also on the relationship between random walk and market efficiency. For some, the rejection of random walk means investors are irrational, "...guided by animal spirit…"[26] or that there is endless opportunity for profits. This collides with the beliefs held by some academics who sustain that markets are perfect. The idea of perfect market has been put forward by Roberts (1959) and then by Samuelson (1965)[27]. According to Samuelson, "in a competitive market there is a buyer for every seller". If one could be sure that a price will rise, it would already have risen"[28]. This assertion bears one of the basic principles of market efficiency, prices incorporate expectation and information and competition amongst investors is the source of market efficiency.

[26] Keynes (1936)

[27] Samuelson (1965) and later Mandelbrot (1966) managed to connect the concept of fair game expected returns and random walk

[28] This gave rise to anecdote of two economists walking down Wall Street when one says to the other "look there is a 100 dollar bill!" and the other replies "it is an illusion, if it were real someone would have picked it up long ago".

According to Lo and Mackinlay[29], Leroy (1973) and Lucas (1978) have demonstrated that in a risk averse world[30] investors “might gladly pay to avoid holding any unforecastable returns”. As a result, a knowledge of the risk associated with current information implies some understanding of the level of expected returns. That is, the efficient market hypothesis might hold, while random walk might not. Grossman and Stiglitz (1980) go even further, sustaining that investors[31] will only spend time and resource in analysing and uncovering information if that activity is likely to generate profits. In a perfectly informationally efficient market, the return for collecting and treating information would be zero, which means there would be no reason to trade. This would eventually lead to market collapse. In light of this way of thinking it is understandable that market efficiency varies across markets and regions. Emerging markets are less analised than developed markets, thus less efficiently priced. The same argument is valid for small stocks compared with large stocks. This, however, is contrary to the belief held by professional academics that regard market analysis as a useless activity, for markets are efficient. What does market efficiency mean, after all?

2.1 Efficient Capital Market

According to Fama(1970), efficient capital market means prices *fully* reflect all available information, and so trading based on information cannot provide abnormal return. The necessary conditions for this to be true would be a frictionless capital market, no trading costs and information acquisition zero[32]. However, in reality, certain information may affect stock market prices more quickly than other information. With this in mind Fama (1970) presented us with the categorisation suggested by Roberts (1967). According to Roberts there are 3 forms/degrees of market efficiency in what regards to information:

[29] A Non Random Walk Down Wall Street
[30] For a risk averse investor it is preferable to have €1 certain in the future, than the uncertainty of the possibility of €2 or €0, with equal probability.
[31] According to them there are two type of investors: the informed investor and non-informed investor
[32] Against this assumption please see Grossman and Stiglitz (1980)

2.1.1 Weak form hypothesis

In its essence means that one cannot use historical prices to predict future prices, or in other words, prices fully reflect all available information implicit in the past prices. This is to say stock prices analysis is a pointless activity.

2.1.2 Semi-strong form hypothesis

Means stock prices reflect all publicly available information. For instance, after earnings announcements market professionals reassess the value of their assets in line with the new information, bearing in mind the possibility of making either profit or preventing losses. It is clear that the main concern on this issue is on the speed with which information is incorporated in the stock market prices. If returns are not predictable from past returns, it simply means that information is incorporated in stock prices at such a speed that professional investors cannot profit from it. They may perceive the changes, but these are already expressed on the prices, thus failing to act on time to make abnormal returns[33].

2.1.3 Strong form hypothesis

Strong form hypothesis is more restrictive than the previous two, maintaining that all information, public or private, is incorporated in the current stock prices. No investor can make abnormal returns. The belief is that there is no one investor with superior information or ability. No one can beat the market all the time. It fails to account for the insider trading, though.

Later, in 1991, Fama reviewed these classifications to encompass not only a more general meaning, but also to account for the criticism made to the previous classification. One of which is the cost of information not being zero[34]. In this new classification he favoured Jensen's (1978) approach in that "…prices reflect information to the point where the marginal benefits of acting on information do not exceed the marginal costs". He reclassified the weak form efficiency in the new, more general category tests for return predictability. The semi strong form efficiency on the more general category of the *event studies or studies of announcements*. The strong form

[33] The same idea was expressed by Samuelson (1965)
[34] Grossman and Stiglitz (1980)

efficiency to the more general category tests for private information trading[35]. To test for the strong form efficiency a group of investors, mainly mutual fund managers, are used to access portfolio's performance[36]. Malkiel (1992) expanded Fama's definition to comprise the effect of information release in the price of the security (if there is no change then the market is efficient) and also to include the evaluation of trading based on information.

The concept of efficient market hypothesis has significant implications for market analysis. For, if stock market prices cannot truly be predicted, then there is no purpose in studying past stock market prices trying to find superior information that can be used in trading strategy. Any trading rules based on these principles are simple a *mumbo jumbo* strategy that can only be profitable by sheer luck, from which follows that technical analysis is useless.

2.2 Implications of the Efficient Market Hypothesis (EMH) for Investment Policy

Considering that some researches had already rejected the random hypothesis[37] in the past, it comes as no surprise that Lo and Mackinlay's [38] rejected random walk in the US market. For them "…equity returns suggest presence of predictable components in stock market…", adding that through active management, superior long term investment returns can be attained.

2.3 Technical and Fundamental Analysis

There are two main schools of professional analysts that agree with Lo and Mackinlay's view. These are professionals that believe there are trends in stock markets. For these professionals there are facts underlying the price formation, these facts are knowable today; they affect future

[35] Studies of the insider trading are both a study of the quality of the insider's information as well as of the SEC's regulation. Insiders are individuals with privileged information about company prospects, managers, stock holders and most of the studies revealed that insider traders gain excess returns. The question is whether these results are consequence of the superior ability or the privileged information, according to Damodaran and Liu (1993). The latter seem to be the reason as many of those who traded and made abnormal return have ended up in prisons.
[36] Cowles (1933) conducted one of the first studies on the subject
[37] Osborne(1962), Cootner (1962) Neiderhoffer and Osborne(1966) in Lo and Mackinlay's Non A Random Walk Down Wall Street
[38] Cootner (1962), Lo and Mackinlay(1988)

prices and can lead to profit if properly understood. The way to find these differs for the Fundamentalists and Technicians.

The Fundamentalist approach is to study external factors behind price changes. In the commodities market, he studies the demand and supply for those commodities. In the stock market, he studies the general business conditions and profit prospects for various industries, earnings and dividends, prospects of the firm, expectations of interest rates, and risk evaluation of the firm to determine the proper stock prices.

The Technician sometimes called chartist, though he subscribes Fundamentalists' basic assumptions, he also argues that the patterns underlying the price formation are reflected in the stock prices. Thus, what is needed is a study of the price movements in the recent past, in order to uncover the signs on the direction of future price movements. He believes that a movement once initiated tends to persist and opposes the idea that the best estimate of the tomorrow's price is through coin tossing. This, however, is exactly what Academics and researchers of speculative markets defend. They argue against price trend in a speculative market, since to academics the apparent trends are a mere interpretation of a random walk process.

Technical analysts use a wide range of techniques[39], but only some of them will be mentioned here. Those are: Moving Average; Relative Strength; Resistance Levels or Support Levels; and Volume Trading. The first two will be dealt with in detail.

2.3.1 Moving Averages

The Moving Averages are highly used by technicians because they are easy to implement and effective. They are used to measure *momentum* as well as support and resistance level. The idea of Moving Averages is to capture market trends in advance. Use a long moving average to capture the general tendency and a short range moving average to establish when to act.

[39] One of the most famous technical analysis theories is the Dow Theory, named after Charles Dow, whose purpose was to identify the long term trends in stock market prices.

The Simple Moving Average (SMA) is actually an arithmetic mean. It involves adding the prices for a number of periods and dividing by the number of periods (e.g. $(X_1+X_2+X_3.....+X_n/n)$[40]. The concern with simple moving average is that it gives the same weight to all observations being considered. In other to accommodate this criticism, a weighted moving average and/or exponential moving average is used. These two techniques give different weights to recent and old observations.

The Weighted Moving Average (WMA) gives each period a weight according to it's "age". The oldest observation is given the weight of 1, the second oldest the weight of 2, and the weight is increased by 1 until the current period is assigned a weight, and are then divided by the sum of multipliers (e.g. $(1*X_1+2*X_2+3*X_3+\ldots X_n*n)/(1+2+3+\ldots n)$.

The Exponential Moving Average (EMA) is used to address the shortcomings of both the SMA and the WMA, including the data number of the period covered by the moving average. EMA gives much more weight to recent observations and ever decreasing weights (lesser importance) to old observations. However, the older observation never disappears, it remains part of the calculation. EMA reacts faster to recent price changes than the simple moving average.

Gama Gonçalves[41], used Moving Averages in his thesis to test for the market efficiency in Portuguese stock market indexes. He studied the BVL (1989-1996) and PSI20 (1993-1996) and found the 1-50 day to be profitable, which is superior to the buy and hold strategy. In order to give power to this finding, Gama Gonçalves then conducted a statistical test in order to assert the significance of results obtained through simulation. The test confirmed the simulation results were statistically significant, however caution should be used when analysing transaction rules strategies. As pointed out by many of Alexander's critics, the use of the closing price can bias the profitability of the trading strategy in the upward direction, as has also been confirmed by Amiud and Mendelson (1987b), for the transaction may not occur at the estimated closing price. Another issue which arises from using stock market indexes: the revision of these stock market indexes. Also to be considered is the effect of dividend on transaction rules. Crato and Lopes (1989, in

[40] The general idea is that we are in the presence of a Bullish market if the 200 days moving average is bellow the S&P500 index, and we are in the presence of a Bearish market in the opposite case.
[41] Tese de Mestrado

Gama Gonçalves) pointed out market microstructure issue that has to do with the short sales. Gama Gonçalves rejected the efficiency for Portuguese stock market, this is consistent with the conclusions by Crato e Lopes (1989) and Borges (1994).

According to Brock et al.(1992) for US and Hudson et al. (1996) for UK, Moving Average shows predictive power for long time horizon. For Hudson, though this result is encouraging in the sense that they have some predictive power, they are not enough to generate abnormal return in a frictionless stock market.

2.3.2 Relative Strength

Relative strength is a strategy that helps select stocks based on their past performance. Contrary to the timing strategy this is a stock selection strategy. The principle behind it is that the past price helps predict today's prices. So, the average daily (weekly) past prices are used to compare with today's prices, if greater than X% buy if bellow K% sell. This strategy tends to include securities with higher risk as they are securities with high variability of returns[42]. These, according to some, tend to be non profitable after accounting for risk and commissions.

Jensen and Bennington (1970) studied the relative strength strategy. Their idea was to develop a high performance portfolio. The result produced a 12,5% returns, higher than the Buy and Hold Strategy. After accounting for transaction costs, the performance was reduced to the same level of performance as the Buy and Hold Strategy. And once the risk is accounted for in the performance of the Relative Strength strategy, it shows to be bellow the Buy and Hold Strategy. These findings led them to conclude that NYSE index behaviour between 1931 and 1965 is consistent with the Efficiency Market Hypothesis.

It should be noted, though, that EMH implies that technical/fundamental analysis is fruitless and predicts failure for both strategies already mentioned. The driving force behind it would be the competition among market professionals, which would make it fruitless. Only analyst with unique insight will be rewarded. The secret lies not in identifying a good company, but on having

[42]Elton and Gruber(1995)

a better than everyone else's estimate. Similarly, identify the company that is not as bad as their stock price suggests.

Historically, technical analysis has been viewed with suspicion by academics in finance, more as a "…..pursuit that lies between astrology and voodoo"[43]. It never enjoyed the same level of acceptance as fundamental analysis.

The reasons for this can be traced to the terms used by one and the other. Whilst fundamental analysts uses words such as earnings, dividends, other balance sheets and income statement items familiar to economists, technical analysts use a different set of vocabulary completely unknown to economists and the public. However, as of late this has been changing, the line that separates technical analysts and fundamentalists is waning, for both of them now use the other's traditional instruments to forecast future prices. The level of acceptance of technical analysis is still low compared with fundamental analysis.

2.4 Test of Predictability in Stock Market Returns

Short term predictability tests whether yesterday's returns can be used to predict today's returns. Earlier tests of EMH were tests of weak form efficiency. The question they were trying to answer was: could speculators find trends[44] in stock market prices and devise a strategy that would enable them to make abnormal returns? This is purely technical analysis.

It was believed then that one way to uncover trends in stock market prices is through the measurement of serial correlation of stock market returns. Serial correlation refers to the tendency for stock returns to be related to past stock returns. A correlation test is of the kind:

$r_t = a + br_{t-1-T} + e_t$ (6),

where a measures the expected return, b the relationships between previous return and current, and e_t incorporates variability of returns not related to previous return. The goal is to establish the

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[43] Lo and Mackinlay's Random Walk Down Wall Street
[44] Kendal (1953) and Roberts (1959) found no evidence of stock market pattern.

linear relationship between today's returns and yesterday's returns. Correlation tests are merely a fitting equation to a set of data. The purpose is to check whether what is provided by the data is what is expected by the model, they are highly sensitive to extremely large observations. Positive serial correlation (see point 2.5 for more details) signifies that positive return tends to be followed by positive return, creating what is know as *momentum* property. Negative serial correlation means that positive returns tend to followed by negative returns, reversal or correction type property. Kendall (1953) found positive serial correlation for daily data of UK stock companies. Cootner (1962) found negative serial correlation for weekly data. Both Conrad and Kauls (1988) and Lo and Mackinlay (1988) studied weekly NYSE returns and discovered positive serial correlation over short horizons. However, they pointed out that the magnitude of the trends is too small to generate abnormal return.

2.4.1.1 Results on Very Short Term Horizons Study

Very short horizons studies suggest momentum in stock market prices, but of small magnitude to be profitable. However, in studies of intermediate horizons on stock price behaviour (3-12 months), Jegadeesh and Titman (1993) found that stock market prices exhibit momentum in which good or bad recent performance continues.

2.4.1.2 Results on Long Term Horizons Study

Contrary to the findings of studies focused on short horizons, long horizons returns studies suggest a negative serial correlation of stock market prices. Indicating there is reversal in stock market prices. This gave rise to the "fads" hypothesis[45], which asserts that stock market prices overreact to relevant news. This overreaction leads to momentum in a short horizon. However, a correction or reversal of the overreaction leads to a poor performance in the long horizon. DeBondt and Thaler (1985) documented return reversal in the long term horizon (3 to 5 years): past losers outperform past winners. For them this is evidence of excessive pessimism following poor performance, making the loser firm a profitable investment. Ball, Kothari and Shanken (1995) follow a different path for explaining the phenomenon, to them poor stock returns performance leads to higher leverage, because the value of stock falls more than the value of the

[45] Bruce N. Lehman (1990), ver estudos de Thaler

firm's debt. The increase in leverage leads to higher risk which in turn leads to higher expected returns than would be reflected in risk estimate from a period before the drop. For others, this is due to a different set of information used by market professionals when assessing the short or long term perspective of a company, thus the seemingly different result. Fama and French (1988a) also found negative serial correlation though they argue that once the 1926-1948 period is removed there is no evidence of negative serial correlation.

2.4.2 Non Parametric Tests

These tests are the firsts to be designed to detect autocorrelation and dependencies in the data. One needs to have in mind that these tests are not powerful. As such, there is a certain tradeoff between the test results and the lost of information.

2.4.2.1 Sequences and Reversals

Proposed by Cowles and Jones (1937), the comparison of sequences and reversals in historical stock returns was similar to the coin tossing probabilities of Bernoulli. Sequences are pairs of consecutive returns with the same sign, and the reversals are pairs of consecutive returns with opposite sign. In a fair coin tossing the sequences over reversals would equal 1. However, in a random walk one with a drift the process is biased toward sequences over reversals, meaning that a sequence over reversals would be greater than one. In this case it is difficult to judge whether a random walk one has been violated[46].

2.4.2.2 Run Test

This is an easy to design test, that it basically examines the sign of price changes. Contrary to the correlation test, the run test is scale free and, as such, not sensitive to large values. A Run is a number of sequences of consecutive positive and negative returns, or runs, which is tabulated and compared against its sampling distribution under the random walk hypothesis[47].

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[46] See Fama, 1965 and Campbell et al.(1997), for further discussions.
[47] See Fama, 1965 and Campbell et al.(1997), for further discussions.

Fama (1966), tested the runs and sequence over reversals and both conformed with what was expected. Run tests and sequencies/reversals are fitting tests. This involves comparing the result with what would be expected under assumption of random walks. Once the sample conforms to the expected, the random walks is considered upheld. Cautions should be used when analysing both run tests and serial correlation tests, for both are tests of linear relationships, meaning they may not capture some more complicated hidden patterns. In this situation it is assumed that no trading rule will be profitable. With this in mind, we will now consider a test design to uncover trends in stock markets: the filter rule.

2.4.3 Filter Rules

To test for Random Walk, Alexander (1961, 1964) used filter rules in which an asset price is purchased when its price increases x%, and sold when its price drops by x%. This is a market timing strategy, that is, they indicate when to take a short/long position making it easier to implement and assess strategies (total return being the metric of success). As mentioned previously (see point 1.3 Page 10) the idea behind these filter rules is that the trends existing in a stock market can be revealed once small movements are filtered out. This dynamic portfolio strategy is taken to measure the predictability of asset returns. A comparison with the Dow Jones and S&P's industrial averages led Alexander to conclude that "….there are trends in stock market prices…".

Although many studies supported the idea of IID of random walks, it should be noted that all these tests only capture the linear dependence (checking correlation coefficient not statistically different from zero is not sufficient). In other words, a process may be considered IID, when in fact it is not. It may not be found any linear dependence, but the underlining process may be generated by a chaotic process or an ARCH type process. In this case the efficiency hypothesis may be questioned if in presence of a chaotic process as the ARCH type process admits dependence in variance (this is in line with the Martingale model[48]).

[48] Curto, Esperança e Reis, " Testes à Forma Fraca de Eficiência dos Mercados: Aplicação dos Índices PSI20, DAX e DJIA

2.4.4 Variance Ratio Test[49]

An important assumption of all three random walk models, mentioned in the beginning of this thesis (see point 1.2.1, 1.2.2 and 1.2.3), is that the variance of random walk increments must be a linear function of the time interval. That is, the variance $r_t + r_{t-1}$ is twice the variance of r_t. Thus, the variance tests the relation between:

$VR(2) = Var[r_t+_{rt-1}]/ 2Var[r_t] = 1$[50] (7);

Positively autocorrelated returns means VR(2) will exceed 1. The opposite is true in the presence of negative first-order autocorrelation.

French and Roll (1986) used this test to study the effect of noise trading. They rejected the market efficiency-constant expected returns model. Lo and Mackinlay, in the study mentioned earlier, used this test to reject the random model for the US market. However, Fama and French (1988a) argue that the variance test for the long horizon provides weak statistical evidence against random walks. Under random walks, the variance ratio should equal unity, however Poterba and Summers (1988) showed that variance ratio declined with time, indicating presence of a mean reverting component. The presence of a mean reverting component in stock prices implies a substantial forecastability of intermediate returns, and therefore substantial differences between price and fundamentals.

Most of the studies discussed here are tests designed to detect a linear structure in financial data. But it is important to stress that finding no linear dependence does not imply absence of a nonlinear dependence. As Campbell et al. (1997) argued "….many aspects of economic behaviour may not be linear and ... the process by which information is incorporated into security prices are all inherently nonlinear." The presence of non linear dependence *per se* implies that markets are not efficient in a weak form[51]. That is, if there is no second order dependence. Brock,

[49] This part of the present work was strongly infuenced by Campbel, Lo and Mackinlay's "The Econoemetrics of Financial Marktes"
[50] See Campbell et al. (1997), for further discussions.
[51] Curto et al. (2003); Afonso, A. and J. Teixeira (1998), Non-linear Tests Of Weekly Efficient Markets: Evidence From Portugal

Dechert and Scheinkman (1987), designed a test henceforth referred to as BDS[52] in order to test for the non-linear dependence of stock returns. There are wide ranges of other tests to be used to determine whether there is or not non-linear dependence in time series. The Engel's test (ARCH models), test for non-linearity in the second moment (variance); Tsay's test tests for non-linearity in mean; Hinich Bispectrum test provides direct test for non-linearity and normality; and finally, the Lyapunov Exponent, which measures the exponential rate at which two nearby orbits are moving apart, characteristic of chaos theory[53].

2.4.5 BDS Test

The BDS statistics is useful to test for patterns that occur more (or less) frequently than would be expected in independent data. It is a non parametric test used to test for non linearity in time series. It is comparable to Box-Pierce test, for they both can provide evidence of serial dependence in time series and both can be used to test the residuals of estimated models. The difference between the two is that the BDS tests for non linearity while Box-Pierce tests for linear dependence.

The BDS is based on correlation integral $Cm(\varepsilon)$ presented by Grassberger and Procacia (1983) (see Appendix 1-Section 2.4.5 BDS), to distinguish between chaotic deterministic system and stochastic system. The test statistics is as follows:

$$W_{m,n}(\varepsilon)=(n[C_{m,n}(\varepsilon)-C_{1,n}(\varepsilon)^{m}])^{(1/2)}/\sigma_{m,n}(\varepsilon) \quad (8)$$

The null hypothesis is: returns are iid and alternate hypothesis need not be specified. It should, however, be pointed out that BDS test statistics depend greatly on the chosen values of ε an m. For large (small) values of ε the spatial correlation between the data points will tend to be high (low). The greater the embedding dimension the smaller will be the number of overlapping histories, and as a result the points defined by embedded vector will become closer and the value of BDS statistics will tend to be higher. Curto, Esperança and Reis (2003) used BDS to test for

[52] This test was developed in Brock, Deckert, Sheinkman and LeBaron (1996)
[53] For more detail discussion on these tests please see: António Afonso, A. and J. Teixeira (1998), Non-linear Tests Of Weekly Efficient Markets: Evidence From Portugal

the efficiency of DAX, DJIA and PSI20 index. They came to the conclusion that the daily return of the three market indexes clearly rejects the iid hypothesis. Afonso and Teixeira (1998) came to the same result for the BVLG, PSI20 and BVL30 indexes. They concluded that the Portuguese stock exchange index is not weak form efficient.

2.5 Market Correlation

2.5.1 Very Short Term Correlation

Neiderhoffer and Osborne (1966) studied market correlations for transactions and discovered some departure from randomness. They also found that reversal in prices, decline after increase, "…was two to three times as likely as price continuation and continuation was more likely after preceding continuation"[54]. This means that once a movement starts in one direction it is more likely to continue in that same direction than to reverse. According to them this is due to market microstructure, the Bid-Ask spread is responsible for the negative serial correlation. The same conclusion Jegadeesh and Titman (1991) arrived at. They provided evidence for a relationship between short term return reversals and bid ask spreads, as did Kaul and Nimalendra (1990) and Jegadeesh and Titman (1995). Jegadeesh (1990), and Lehman (1990) also found evidence for short term reversals. They showed that contrarian strategies based on the previous week/month returns generate significant abnormal returns. These strategies are transaction intensive and based on short term price movements, and they may be a reflection of short term price pressure or lack of liquidity in the market rather than overreaction.

2.5.2 Correlation for a Portfolio of Securities

Because of the variance reduction obtained through diversification, portfolio returns provide more powerful tests of predictability using past returns. However, this increased power may be offset by upward biased autocorrelations induced by nonsynchronus[55] trading or infrequent trading of securities in the portfolios (Fisher, 1966).

[54] Fama (1970), pp. 396.
[55] Nonsynchronus trading or none trading arises when time series are taken to be recorded at time intervals of one length when in reality they are recorded at time intervals of other, possibly irregular, lengths. Reference to "daily prices" leads one to think that prices are spaced 24 hours intervals, giving the false impression that there is predictability in where there is none.

Lo and Mackinlay (1988), Conrad and Kaul (1988), showed evidence of serial correlation in weekly returns. This correlation is stronger for small stocks. On correlation of securities due to thin trading[56] important information may affect individual returns on different times, thus generating correlation where, in reality, none exists. This is consistent with the fact that portfolio of small stocks has higher correlations than large portfolios. Konrad and Kaul (1988) examined autocorrelation from Wednesday to Wednesday, in order to eliminate the effect of nonsynchronus trading. They reached the same result as Lo and Mackinlay (1988).

2.5.3 Correlation Over Longer Horizons

Fama and French (1988) and Poterba and Summers (1985) found negative serial correlations over longer horizons. DeBond and Thaler (1985) and Chopra, Lakonishok and Ritter (1992) reported return reversal over the period of 3-5 years for NYSE stocks. That is to say that stock that performed poorly over the past 3-5 years achieved higher return than stock that performed well over the same period[57]. Some argue against these results, using systematic risk and the size effect (Chang, 1988, Ball and Kothari, 1989 and Zarowin, 1990) to account for the success of the contrarian strategies. Lakonishok, Shleifer and Vishny (1994) suggest market irrationality[58] (waves of pessimism or optimism that affect investors) before returning to their true value. An interesting fact is that long term losers outperform long term winners only in January, casting doubts whether the result is due to market overreaction. There are other explanations provided for this phenomenon: changing of expected returns, mean reversion, and market microstructure biases are particularly serious for low priced stocks (Ball and Kothari, 1989); book to market ratio effect (Chan, Hamao and Lakonishok, 1991).

[56] Fisher (1966)
[57] This gave rise to the so called contrarian style investing, where you buy the past losers and sell the past winners. Fama and French (1996) used the multi-factor model to study this phenomenon and find no evidence of abnormal returns. Concluding, thus, long term reversals are consistent with the multi factor model.
[58] See Shiller(1981,1984), Fisher Black(1986), Grinblat, Titman and Werners (1995) and Scherfstein and Stein(1990)

Chapter 3

3 Selected Empirical Irregularities or Market anomalies

Although the majority of the research suggests markets are efficient in what respects to information set, it should be noted that a number of studies have revealed seasonal anomalies on asset returns, meaning some departure from market efficiency. Put differently, there are patterns in security returns not predicted by modern financial theory. The numbers of anomalies documented are so large that the focus will be directed only to those more robust and common throughout other markets. Market anomalies arise from empirical tests of joint hypothesis involving market efficiency and returns behaviour according to the equilibrium model, Capital Asset Pricing Model (CAPM). Due to this joint hypothesis test it is difficult to pinpoint the reason for the anomaly whether it is a result of market efficiency or incorrect equilibrium model. The persistence of some anomalies, however, suggests that the problem lies not in market inefficiency rather in the equilibrium model that cannot describe market reality in its entirety, for if the anomalies were due to market information they would have been eliminated by active traders.

Under Sharpe (1964), Lintner (1965) and Mossin's (1966) equilibrium model or CAPM the expected returns on risky assets should be determined by the covariance of their returns with the return on the market portfolio. The model is presented below:

$r_a = r_f + \beta_a(r_m - r_f)$ (9),

where, $r_{f;}$ is the risk free rate; β_a , $\beta_a = \sigma_{am}/\sigma^2_m$ (10) is the beta of the security, or measure of risk relative to market portfolio or the security responsiveness to movements in the market portfolio; r_a is the expected market return; and $(r_m - r_f)$ (11) is equity market premium.

It is assumed that markets are efficient and the participants are homogeneous and are mere price takers. As such they are expected to "…accept the prices as given, no more, no less"[59]. This

[59] See, for instance, Brealey and Myers (1998), pp. 337, paragraph. 2

implies that the prices process is exogenously given and the model is more of the investors' optimal choice rather than a model of return generating process.

3.1 Calendar anomalies

3.1.1 Monday and Days of the Week Effect

French (1980), Gibbons and Hess (1981), provided evidence for the "Monday Effect". They find Mondays to have lower returns than the average of the other days of the week (for the USA stock market), large negative Monday returns. In Australia, Korea, Japan and Singapore the same phenomenon has been documented on Tuesday, perhaps due to time zone difference relative to US and Europe[60]. According to some authors this phenomenon is due to the information release to the market, because companies usually tend to deliver the bad news after markets close on Friday (weekend effect) and the effect is felt next Monday, when the markets open. However, if the news is good for the company, the announcement is usually anticipated. The strategy in this kind of situation is to avoid taking long positions on Fridays.

3.1.2 January Effect

The most researched of the seasonal anomalies is the January effect; it is particularly evident on the first week of January. It has been documented throughout the world equity market[61]. Returns in January are higher than the rest of the months, especially for small stocks: they appear on average higher in January than in the rest of the months

There are many explanations for this anomaly. Keim (1983) and Reiganum (1983), the firsts to document this anomaly, noticed that these abnormal returns occur in the first two weeks of January. Keim provides *market microstructure* to account for the January effect. According to

[60] It has also been studied in the Turkish market by Aydogan and Both (2003): foreign exchange markets and exchange rate changes are higher on Tuesdays and Wednesdays. Jaffe and Westerfield (1989) also reported seasonal anomalies in other markets.

[61] Barone (1990) for Italy; Tinic et. al (1990) for the Canadian Market; Aggarwal et al. (1990) for the Japanese market. Chordia and Shivakumar (2005) also documented this fact.

him this is due to the fact that prices are at bid in December and January closing price at ask, this is more pronounced in small cap stocks as they have a wider bid-ask spread[62].

Some authors suggest the *tax selling hypothesis*[63], according to which investors tend to sell stocks they suffered significant loss with, at the end of year, thus incurring in tax losses. They do not put the proceeds of the sales in the stock market until the beginning of the next year, when they buy stocks to invest. In doing so, they exert price pressure, causing the prices to rise and thus the January effect. Though interesting, this explanation fails to account for the phenomenon in at least the Australian market, a country with a different fiscal year.

Others, like Haugen and Lakonishock (1988), suggest *window dressing* as the cause for the January effect. This refers to the impact of institutional investors' "*window dressing*" at the end of the year, selling off loser stocks that have declined in price so they do not appear on the year end statements. It has been argued of late that the January effect is waning. Contrary to most studies Gu (2003) finds not only a declining January effect, but also that it affects large stocks more than small stocks. This fact suggests January the effect does not have to do with size.

3.2 Returns and Firms Characteristics

Under the efficient market hypothesis it should not be possible to make excess returns by studying a specific firm's characteristics. To deal with apparent market anomaly some explanations have been provided with the purpose of shedding some light in to it. There are basically three explanations to it: 1) data mining[64], which is that when so many researchers are studying the same data, some relationships is bound to be found; 2) ignored firm characteristics, some risky variables not taken into account on the study may explain the excess returns – small firms exhibit excess returns when measured through CAPM, some researchers argue that this is

[62] Blume and Stambaugh(1983), " bid-ask spread induces upward biases in returns calculated with transaction retuns" and also Roll(1983) points out that the selling pressure reduces the price of small cap firm in December, whilst the opposite would occur in January when investors repurchase these stocks.
[63] Ritter (1988)
[64] See Lo and Mackinlay's "Random Walk Down Wall Street" for detailed description on the subject and Lo, A. W. and C. A. MacKinlay (1990)

due to low survival probability, which is not properly captured by CAPM's betas[65]. Once this is accounted for the size effect disappears; 3) finally, misestimation of CAPM can cause large unexpected returns where none exist. Suppose that betas for small companies are systematically underestimated. This would mean that the expected returns for these companies would be too low, however they would exhibit excess return when betas are properly estimated[66].

3.2.1 The Size Effect

The size effect refers to the negative relationship between security and market value of common equity of a firm. Banz (1981)[67], was first to document that small firms would have earned excess return in the period of 1936-1977. He also found the coefficient on size to have more explanatory power than the beta coefficient in describing the cross section of returns. In later studies other researchers discovered that the excess returns for small firms occurred mainly in the month of January. This led them to argue that this is due to underestimation of small firm betas, as mentioned earlier. The reason for this, according to Roll[68] and Reiganum (1983)[69], small firms' betas are biased downwards, because thin trading and nonsynchronous trading. The other explanation for the phenomenon is provided by Christie and Hertzel[70]. They reason that considering betas are estimated based on the past prices, the changes in the firms' economics means they are much riskier today then they were yesterday. Amihud and Mendelson (1986) argue that the size effect is a premium for low liquidity firms, small firms to be precise.

A second reason for explaining the firm effect is that CAPM miscalculates the excess returns. In support for these ideas there is study by Chan, Chen, and Hsie (1991) using the APT model. They found a 1,5% per year excess returns between small firms and large firms, contrary to the 11,5% found through the CAPM model. In the views of Amiud and Mendelson (1986) the reason why investors should demand higher excess return from small firms has to due with the difficulty in

[65] This is because when 5 years are used there are firm size effect, this disappears when longer period are used (See Chan and Chen, 1988)
[66] Ball (1978), "..may be the result of CAPM misspricing rather than market inefficiency".
[67] Rolf Banz, "The relationship between market value of common stock", Journal of Financial Economics 9 (March 1981)
[68] Modern Portfolio Theory and Investment Analysis
[69] Marc R. Reiganum, Size related anomalies and the stock market return seasonality: further empirical evidence," Journal of Financial Economics 12 (1983)
[70] Modern Portfolio Theory and Investment Analysis

trading these stocks. Some researchers argue that the high trading costs of small stocks do not necessarily mean inefficiency, rather an adjustment to risk associated to small firms.

3.2.2 Announcement and Price Return

One of the bedrocks of the market efficiency hypothesis is the rapid adjustment of prices to new information. Thus it is understandable that great effort and resource have been committed to the study of the effect of announcement on a share price. These studies called “event studies”, as they examine the effect of a particular event on a stock price, are designed to capture the speed to which stock market prices adjust to these new information, thus determining whether markets are efficient or not. Although most of the studies favour the market efficiency hypothesis, it should be noted that there are documented cases of sluggish response of stocks price to firm’s announcement. This is called Market underreaction to earnings-related information. This suggests that the sluggishness of market participants is due to the prolonged adjustment of analyst forecasts. The inertia in revising forecast may not be helping the market to assimilate new information in a timely fashion. This point of view (sluggishness) is reinforced by studies of Givoly and Lakonishok (1979)[71].

3.3 Momentum Effect

Profitability of momentum strategies is one of the strongest and most puzzling asset pricing anomalies. Momentum is puzzling from the market efficiency perspective, because it suggests that risk increases following positive stock returns, contrary to the intuition that leverage and equity risk should both decline.

Stocks with prices on an upward (or downward) trend over a period of 3-12 month have higher expected probability of continuing on that trend over the next 3-12 months[72]. This is referred to as *momentum or continuation*. Jegadeesh and Titman (1993) showed that strategies that buy past winners and sell past losers generate significant abnormal returns. This anomaly has been

[71] Chordia and Shivakumar(2005), documented post earning announcements drifts, where superior performances persist over the next 6 months after announcement.

[72] Jagedeesh and Titman (1993). It should be emphasized that the first to refer to momentum in stock market is Cowles and Jones (1937). They notice that stock that advance in one month tend to have the same behaviour next month.

documented in many other markets[73] and has persisted over the years. Finding risk-related explanation for the phenomenon has proven difficult.

Fama and French (1996) used the three factor model to account for the continuation documented by Jeagdeesh and Titman (1993). However, they could not explain *momentum* in stock markets. Although the multi factor model is consistent with long term reversals. They find that risk adjustment tends to accentuate, rather than explain, momentum profits.

There are many competing explanations for momentum in the stock market returns. Chan, Jegadeesh and Lakonishok (1996) argue for underreaction; Chan (1988) and Ball and Kothari (1989) suggest the equilibrium model does not properly account for the risk factor and suggest return continuation due to misspecification of CAPM; Lewellen[74] suggests cross-serial correlation among stocks (correlation between an asset's return and the lagged return on other asset as the explanation for the phenomenon). Lo and Mackinlay (1990) argue that part of this abnormal return is due to a delayed stock price reaction to common factor rather than a momentum due to overreaction induced by "positive feedback trading", trading strategies of the sort documented by DeLong, Shleifer, Summer and Waldman (1990). This explanation implies that the trend "chasers" reinforce movements in stock price even in the absence of fundamental information, so that the returns for past winners and losers are temporary in nature. However, small signs of reversals suggest that the feedback trading does not account entirely for the profitability of the momentum strategies. Some suggest improper market response to new information, others market microstructure biases, bid ask spread and data snooping biases. The existence of momentum in stock market created the strategy called momentum style investing. This seems to be the favourite style of investing by mutual fund managers, according to Gringlatt, Tittman, Werners (1995).

[73] See K. Geert Rouwenhorst, "International Momentum Strategies", The Journal of Finance, Vol. 53, 1 feb. 1998, pp. 267-284

[74] Jonathan Lewellen, "Momentum Profits and the Autocorrelation of Stock Returns**",** MIT Sloan School of Management

3.4 Market Rationality

It is a common assumption that market professionals are rational agents. This is to say, they assess securities and decide to purchase/sell based on the level of risk and return. They are concerned with whether the market prices reflect the expectation of securities current value of cash flow. However, it is now a well known fact that not all agents in the market behave rationally. It is also assumed that there are few of these types of agents in the market and that they tend to disappear as a result of the arbitrage of the more rational and informed investors. In sum, they are considered irrelevant to the well functioning of the market. This principle is ingrained in the informational efficient market hypothesis; although it is been challenged of late. Several studies have shown that not only some irrational investors trade on other things (noise) rather than information, but they also are successful. Instead of suffering from the effect of arbitrage they actually benefit from the actions of rational investors. At this point it should be pointed out that not all traders are aware they are trading on noise or information[75].

Today it is commonly accepted that investors tend to undereact/overreact to information. Contrary to the academics' beliefs, professional investors and institutional investors sometimes tend to act on the basis of their fads. Shiller (1984) notes that the institutional investor "…reads the same books, news, researches…" and so, "…their behaviour in regard to market decision tend to be similar". Findings by Grinblatt, Titman and Werners (1995) support this idea also, according to them mutual funds tend to herd and tend to buy stocks based on their past performance (momentum strategies), predominately buying past winners. If either irrationality or agency problems generate these trading styles (Scherfstein and Stein, 1990), then mutual funds that exhibit these behaviours will tend to push the purchase prices of stock above the intrinsic values thereby realising lower value. However, if this type of behaviour arises because informed portfolio managers tend to pick the same underpriced stocks, then funds that exhibit these styles should realise high future performance.

[75] See Black (1986)

3.5 *Large Volatility*

The idea of market rationality is challenged when changes (volatility) in market price deviate considerably from the price change in prices fundamentals, high volatility of assets prices relative to fundamentals. Shiller (1981)[76], argues that volatility verified in price change cannot be accounted for the simple information regarding the discount. The logic behind this reasoning is that the models implied returns should be unforecastable and also implied that assets prices should be less volatile than dividends. Empirical studies, however, show evidence to the contrary, that is, dividends are less volatile than stock prices. Another aspect reported regarding this phenomenon is the feedback trading[77] as the cause of market bubbles and increase in volatility. It is also admitted that the *animal spirit* plays an important role on the issue of price formation. For it cannot be argued or justified, for that matter, why prices do fluctuate such when dividends (or any company fundamentals) are stable in the long run. Explanation put forward to account for the phenomenon according to Leroy (1992) is investors under-over reaction[78] to information and for DeBondt and Thaler (1985,1987) is investors' tendency to ride loosers to long and sell winners too soon. Evidence of over-under reaction can be traced to many different event studies. It is a well known or commonly admitted that after earnings announcements there is a period during which prices are sluggish and that it takes sometime to the new information to be reflected in the share prices.

[76] Robert J. Shiller, "Do Stock Prices Move too Much To Be Justified by Subsequent Changes in Dividends?", American Economic Review. Against this view, please see Kleidon (1986) , Marsh and Merton (1986) that questioned the validity and robustness of the statistical methods used by Shiller. For Schwert, however, "…this not as much anomaly or inefficicency as it is a result of the model evaluation used".

[77] Feeback trading means market participants act on the same direction, increasing the deviation of the price from the true value

[78] For more details on over-under reaction, please see Barberis, Shleifer and Vishny, "A Model of Investors' Sentiment, in Advances in Behavioral Finance, Vol II; Daniel, Hirshleifer and Subrahmanyam, "Investors Psychology and Security Market", in Advances in Behavioral Finance Vol II.

CHAPTER 4

4 Empirical Study

4.1 The Data

The data used in this study was taken from the Data Stream data base[79]. The criterion used to select the market indices for empirical test and simulation strategy is the Data Stream market capitalisation for the year 2006[80]. The Data Stream database provides us with the countries market capitalisation, thus our job was to select the most significant and liquid index in each of these markets. This aspect is of great importance for technical analysis as it allows simulating in a more realistic environment.

The data for the study consists of daily closing prices (not adjusted for dividends) in United States dollars (we converted the local currencies to US$, whenever these indexes are not expressed in US$) and the compound returns. The reason for using compound returns has to do with the characteristics of log returns, contrary to the use of simple returns and closing prices. Prices are generally non stationary[81] and as such they do not have the desired property for studies; they are sometimes stable and others highly volatile. There are important characteristics compound returns exhibit and that are seldom present in prices: stationarity and ergodicity. Another important aspect of returns is that they are scale-free, contrary to prices. The continuous compounding of single period returns r_t are IID normal.

As the purpose of the study is to evaluate market efficiency in the global market, we used indices belonging to the five continents. In addition to the indices selected through Data Stream market capitalisation criterion, we also included some more indices from other countries so to have a very global portfolio. For each country we only selected one market index, the only exception, to this rule, being the USA. For the USA we chose two more indices, since they are extensively

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[79] The software used is EVIEWS 5.0
[80] See the appendix 4.2 for more detail Appendix 4.
[81] Stationarity mean a process is not affected by change of time origin. Formally, this is to say that the distribution of Y_1 is not the same as that any other Yt. In others words, the joint probability distribution at any set of time is not affected by a shift along the time.

studied indices. In Total we selected 50 stock market indices around the globe: from Africa (South Africa FSTE/JSE 40, Nigeria S&P/IFCG*, Kenya NAIROBI SE, Morocco SE CFG25), Latin America (Argentina Merval Index, Brazil Bovespa, Chile General IGPA, Peru Lima SE IGBL, Mexico IPC Bolsa), North America (Canada SP/TSX Index, USA DJIA*, USA SP500*, USA NASDAQ100*[82]), Asia (China Shanghai Composite, Hong Kong Hang Seng Index, India BSE National 200, Japan Nikkei 225 Stock Average, Korea Kospi 200, Australia SP/ASX 200 PI, Indonesia Jakarta SEC, Malaysia KLCI Composite, New Zealand NZX All PI, Philippine SE Index, Singapore All, Taiwan SE 100, Thailand Bangkok SET 50) , Eastern Europe (Poland Warsaw General, Czech Prague SE PI, Russia RTS Index), Middle East (Israel TA 100, Kwait All Share General, Saudi Arabia SP/IFCG, Bahrain Dow Jones), Europe (Nederland AMEX Index, Denmark OMXC 20, Finland OMX Helsinki 25, Ireland SE Overall Index, Luxembourg SE General, Sweden OMX Stockholm 30, Switzerland Swiss Market Price Index, Euro DJEurostoxx50, France CAC 40 PI, Germany DAX 30, Greece FTSE ATHEX 20, Turkey ISE National 100, Italy SP/MIB PI, Portugal PSI 20, UK FTSE 100, Spain IBEX 35, Norway OSLO SE OBX). The majority of indices are from developed countries and from Asia emerging markets.

In order to pursue the purpose of this thesis, as mentioned above, we tested for nonlinear dependence in stock market around the world equity markets, as this can lead us to conclude on the global market efficiency or not. We used the longest series available in the Data Stream for each of the existing indexes being studied. We have not tried to adjust the indexes to the same time frame, for instance all series starting in January 2000 to December 2006), as most of the nonlinear tests require longer series in order for it achieve some meaningful conclusion[83]. The adjustments to the same time frame, however, were made in the simulation strategy we conducted (this is to be mentioned later in more detail). The longest series for the empirical study is the Dow Jones Industrial Average with 14608 observations starting from January the 2nd 1951 to December 29th 2006; the shortest series is the Kuwait All Share General with starts at 12th of May 2000 and ends at 29th of December 2006.

[82] Stock market indices denominated in US dollar

[83] It should be noted that long series can create the nonstationarity issue over longer time span. We are assuming stationarity throughout all the sample period in consideration. This problem could be solved through high frequency data, at each minute, for instance. However, we would then be unable to make this a global study as the availability of data for some of the market indexes is non existing for that time frame. And there is also the microstructure aspect to consider. This kind of data exhibit bid-ask bounces and other market microstructure.

4.2 Non Linear Dependence

Most of the market efficiency tests were tests of weak form efficiency. The run tests and correlations tests were used in order to determine whether the series were independent or not (see point 2.4.2.2 for more detail). The independence test is accepted whenever the price series is generated by random walk model given by:

$LnP_t=C+LnP_{t-1}+\mu_t$ (12);

where μ_t is an IID random variable with zero mean and finite variance (often called "white noise") and C is a constant drift. When this condition is verified, LnP_t follows random walk, and the weak form efficiency is upheld.

However, caution should be put into reading these kinds of results, as linear independence does not rule out the non linear dependence and the presence of non linear dependence calls into question the random walk model. The simple statistics/traditional tests of autocorrelations different from zero (as presented by Kendal, 1953) and others during the beginning and mid 20th century as proof of market efficiency or unpredictability of market returns) is not sufficient[84]. It is therefore required to test for non linear dependence in the series, to verify whether what is taken for random walk is not a nonlinear process which *looks* random (chaos).

The interest on nonlinearity has been increasing over the past years, first because the nonlinearity model has been used in an attempt to improve the forecasting accuracy of linear models, secondly to explain some aspects of the economic activity more than that permitted by linear models (explains fluctuations in the economy and financial market that appear random), and finally because of the market efficiency implication of nonlinearity, which questions the underlying linear model assumption. "The presence of well behaved nonlinear structure would be inconsistent with market efficiency, if accompanied by risk-neutrality and negligible transaction costs." this according to Abhyankar et al. (1995). Many studies have documented nonlinearity on economic activity, starting with the pioneer works by Hsie (1989). The idea is that the world is

[84] See Fama (1965, 1970), Mandelbrot (1963) and Hsieh (1989)

governed by highly complex chaotic processes, which we may never detect using finite amounts of data, meaning that there is no difference between deterministic chaos and randomness. However, if this is not the case, and the world is governed by low complexity chaos, then short term predictability should be possible, but not through linear models.

There are mounting researches evidence supporting nonlinearity, though very little in favour of chaos. Until recently it was more or less taken for granted that movements in stock market prices are stochastic in nature, if not actually random walk. And it seems unlikely that a pattern in stock market returns could be explained by a deterministic process, given the assumption that price movement in stock prices is due to the flow of news. However, nowadays, there is a broad agreement that nonlinear structures exist in financial series. This assertion is true for exchange rate markets (Hsieh, 1989), and precious commodity markets (Frank and Slango, 1989). There are also some evidence on low dimension chaos (see Mayfield and Mazrach, 1989) and Hsieh (1989,1993). Uncovering this phenomenon his due to the effort on the part of researcher, which upon observing some departure from efficiency Fama (1991) and Lo and Mackinlay (1989) and others, tried to find plausible explanation for the phenomenon and these actions led to the creation of a set of tests capable of detecting nonlinear pattern in time series data. It became clear that many low dimension deterministic processes outputs are similar to white noise's. This implies that one may be led to infer on the assumption of random walks when the process is in fact not a random walk[85].

4.2.1 Nonlinearity Tests

Like random theory and price trend theory in the beginning of the 20th century, nonlinearity has not lacked in controversies. Many economists still believe that the assumption of linearity is a plausible representation of the economic reality, in spite of the mounting evidence in support of nonlinearity against the linearity assumption. Nevertheless, controversies persist because the nonlinearity detected by various tests in time series data could not be explained: the available tests cannot provide an explanation for the source of the chaos or nonlinearity observed. This is

[85] Hsieh (1989) provides an example of nonlinear model that can be wrongly interpreted as IID. This is a nonlinear model proposed by Engle (1982): Xt=εt. This time series exhibits low or no correlation, though it is not independent from xt-1.

one part of the controversy; the other is the set of tests used to study the nonlinear phenomenon. There are a variety of tests of nonlinearity, we have mentioned a few earlier on the point 2.4.5 , each of which with a different null hypothesis, being difficult to compare the power of one over the others and the power of the tests itself (see Appendix 2- Section 4.2.1) for comparison of the tests). According to Barnet and Serletis (2000) each test examines a slightly different issue and that at best are complementary rather than competing. So in selecting one test over the other one is testing a slightly different aspect of nonlinearity. Perhaps the best solution would be to use each test where they perform best.

Amongst a variety of tests available: Engle's, Tsay, Hinich bispectrum, the Lyapunov exponent the BDS statistics, NEGM's, White's and Kanplan's test. We chose the BDS test first because it stands out in terms of power against a variety of alternatives, and secondly because, along with the Hinich bispectrum test, it is the most used test to study financial time series[86]. Its drawback is when used in small samples. As mentioned, before the alternate hypothesis is not specified, meaning that a rejection of iid (null hypothesis) does not provide the alternative model one should consider. Rejection of iid can signify the presence of nonlinear dependence, either deterministic, chaos type process or stochastic, or simply nonstationary. Thus, additional diagnostics tests are needed in order to uncover the source of the rejection, please refer to point 2.4.5 for more detail.

4.3 Description of the Methodology

We converted the prices into dollars and then we calculated the log returns through the relationship:

$r_t = 100*\ln(P_t/P_{t-1})$ (13);

where p_t is closing price of the index on day t, and p_{t-1} is closing price of the index on the previous trading day.

[86] Other simulations have shown BDS to have more power against a large variety of alternatives, including the ARCH type models, see also, Chris Brooks (1999), "Portmanteau model diagnostics and tests for nonlinearity: A comparative Monte Carlo study of two alternatives", Computational Economics.

Through this procedure we create a new time series by transforming stock indexes into a series of continuously compounded returns, to which we applied the Box-Jenkins methodology generating the Auto Correlation Coefficient Function (ACF) and Partial Auto Correlation Coefficient Function (PACF). These results were then used to determine the adequate ARMA (p,q) (for example of an ARMA model, please see the Appendix 3 – Section 4.3) type model.

In selecting the ARMA model, we value the model that maximises the log likelihood function and also have in consideration the Akaike (1974) and Schwartz (1978) information criterion. After the more adjusted, or parsimonious ARMA model has been selected, we follow to the next step[87]. We then generate a new series with the fitted residual and applied the BDS test to the residuals[88]. The tests of non linearity, except for the Hinisch bispectral, all shares the same principle: once any serial dependence is removed from the data through filtering, any remaining serial dependence must be due to non linearity generating mechanism[89]. Thus, each of the procedures is in fact a test of serial independence applied to the serially uncorrelated fitting errors of an AR(p) or MA(q) or ARMA(p,q) model for the sample.

4.4 Empirical Results

4.4.1 Statistical Properties of Rates Returns

Before we proceeded to the formal nonlinear tests, we performed a preliminary analysis on all the stock market indices return series, in order to get a view of some important statistical features of these series of returns. Assets returns are known to be leptokurtic, asymmetric and sometime display volatility clustering (tendency for highly/low volatility to be followed by similar volatility), tendency for volatility to be in a specific period of time (Mandelbrot, 1963) and Fama (1965) also noticed that "…large daily price changes tend to be followed by large price changes".

[87] . It should be noted that our purpose is not to build a statistically adequate empirical model of stock index returns, rather to select an acceptable specification, which will remove autocorrelations from the returns series. More importantly, we aim to generate a residual with no serial dependencies.

[88] The use of residuals, instead of the raw data, does not alter the assynptotic distribution of the BDS test (see, Hsieh, 1991 for further discussion)

[89] This procedure was suggested by Grassberger and Proccacia (1983)

We checked whether these stylised facts are present in all market indexes. Please, refer to the Table 1 for the preliminary statistics.

Table 1 of the descriptive statistics
(Please see the Appendix 5 – Section 4.4.1 for the full results)

	Decriptive Statistics								
Indices	Obs.	Mean	Med	Max.	Min.	Std.	Skew	Kurtosis	Jarque-Bera
Argentina M	3499	0,01	0,04	17,79	-33,65	2,41	-1,06	20,18	43665,63
Nigeria IFCG	3000	0,08	0,04	10,28	-10,44	1,10	-0,06	12,33	10880,33
S.A. FTSE T 40	3000	0,03	0,07	8,78	-15,10	1,53	-0,69	10,35	6.985.588
China Shanghai C.	1175	0,04	0,00	7,84	-5,73	1,22	0,46	6,01	486
Japan NIKKEI	13021	0,03	0,00	13,31	-19,26	1,26	-0,34	16,15	94030,29
Russia RTS	2955	0,10	0,04	15,56	-21,10	2,79	-0,49	9,75	5.725
S. Arabia SPIFCG	2347	0,06	0,00	16,01	-13,21	1,40	-0,82	24,58	45818,1
DJEurostoxx50	5217	0,03	0,07	7,57	-10,14	1,21	-0,28	7,66	4.780
Portugal PSI20	3651	0,04	0,04	5,93	-8,24	1,07	-0,28	7,01	2.494
UK FTSE 100	7543	0,03	0,02	12,67	-17,60	1,14	-0,52	23,11	127500

The main conclusion we draw from this preliminary analysis is that all the stock indices exhibit the same stylised characteristics already mentioned. That is they are leptokurtic, the value of the test statistics are greater than the value for standard normal distribution's leptokurtosis (Gaussian distribution's leptokurtosis value is 3). They are asymmetric which can be seen from the table, all values are different from zero (the Gaussian distribution value). Not surprisingly, given the non-zero skewness levels and the excess kurtosis demonstrated within these series of returns, the Jarque-Bera(JB) test strongly rejects the null normality for all the indices. These results conform to the general consensus that the distributions of stock market returns are non-normal.

4.5 The BDS Test Result

Most of the models estimated are of ARMA(1,1) type models[90], as in Hsieh(1989). There are some white noise models also. Whenever we encounter a white noise we checked AR(1), MA(1)

[90] We have not provided evidence of the additional models as they are trivial for the purpose of this study.

and ARMA(1,1)[91] we verify whether the results are genuine or model specification error. After which we applied BDS test. Please refer to the table 2 for the result of the test.

Table 2 BDS Test Results (for full result, see the appendix 6- Section 4.5)

	BDS Statistic			Std, Error			z-Statistic		
Indices/Dimension	4	5	6	4	5	6	4	5	6
Brazil Bovespa	0,067	0,079	0,087	0,002	0,002	0,002	28,254	32,347	36,616
China Shanghai SE C.	0,102	0,117	0,123	0,003	0,003	0,003	31,161	34,072	37,066
Djeurostoxx50	0,054	0,061	0,064	0,002	0,002	0,002	23,025	25,187	27,307
Kenia Nairobi SE	0,071	0,075	0,076	0,003	0,003	0,003	23,107	23,551	24,543
Malyasia KLCI Com	0,083	0,094	0,099	0,002	0,002	0,002	35,983	39,193	42,422
Portugal PSI 20	0,051	0,058	0,060	0,003	0,003	0,003	18,614	20,103	21,536
Saudi Arabia SP/IFCG	0,045	0,049	0,058	0,005	0,006	0,005	84,766	87,987	10,826
Singapore ALL	0,063	0,071	0,074	0,002	0,002	0,002	27,196	29,523	31,936
UK FTSE 100	0,122	0,146	0,161	0,002	0,003	0,003	49,308	56,518	64,287
US DJIA*	0,000	0,000	0,000	0,000	0,000	0,000	-0,009	-0,011	-0,013

*The value of probabilities for USDJIA for the 4,5 and 6 dimension are 0,993, 0,992 e 0,989.

The BDS test rejected the idea of IID of returns for all stock market indexes, except for USA DJIA[92], these results are significant at 5% intervals confidence, reinforcing the held belief that stock market indexes or stock market returns are non linear in nature or have a significant non linear component . These results do not imply market inefficiency. Because, although, returns are not iid, implying potential predictability, this is not to say forecast error are predictable. The predictability of forecast error would imply market inefficiency. The rejection of iid is consistent with the view that returns are generated by nonlinear stochastic processes, ARCH type models. These results are consistent with the results by Joe and Menyah (2003)[93] for the African markets, Meza, Bonilla and Hinich (2005) for the Chilean stock markets, Lim, Azali and Hinich (2005a)[94] using Hinich bispectrum test, for the Nikkei 225 (Japan), Hang-Seng (Hong Kong), Strait Times

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[91] It is always ideal to use low order linear filter as approximation to non linearity, and tests of low dimensional chaos. This according to Bickel and Buhlman (1966) distinguishing linearity and non linearity of a stochastic process may become impossible as the order of linear filter increases.with that in mind we tested for low order filters
[92] This rejection may be due to regime changes (nonstationarity in return series). It is difficult to argue that over long horizon stock returns remain unchanged in mean returns due to changes in economics fundamentals.
[93] Joe and Menyah (2003) used a logisitc map to study non linear dependencie for 11 African stock markets, the 4 african markets selected are also part of the 11 sudied by these authors.
[94] The authors used both BDS and Hinich Bispectrum test

(Singapore), Kuala Lumpur Composite Index (Malaysia), Amermman and Patterson (2003) for Taiwan, Dias Curto et al. (2003) and Afonso et. Al(1998) Portuguese market index PSI20;. Abhyankar et al.(1995) for UK market, Dias Curto et al. (2003), Kosfeld and Robé (2003) for Germany DAX 30, Antoniou et al. (1997) for Turkey ISE National, Panagiotidis (2004) for Greece FTSE/ATHE and Hinich and Patterson (1985), Hsie (1989,1991) for the US market indices.

In addition to BDS test for non linearity, we also tried to find explanation for the non linearity (iid) observed in the behaviour of stock indexes returns series, as the rejection of iid *per si* is of no great use, if we cannot find the source of the rejection or at least the explanation for the rejection. Because BDS test has power to detect linear dependence (this has been moved removed through filter so focus on the rest), nonstationarity, chaos and nonlinear stochastic processes. In that sense we performed two additional tests over the fitted residuals: Engle LM test and Mcleod-Li test.

4.6 Mcleod-Li Test

This test is designed to detect nonlinear dependence in a time series. It was proposed by Mcleod-Li (1983), and it is based on the Box-Pierce and Ljung-Box statistics. The test is conducted over the square of the fitted residuals, like the Engle's LM test.

Table 3: Mcleod-Li test Result (for full result please refer to the Appendix 7- Section 4.6)

	Mcleod-Li Test Result			
Indices	F-statistic	Probability	Obs*R-squared	Probability
Brazil Bovespa	3,905	0,020	7,805	0,020
Canada SP Index	4,959	0,007	9,913	0,007
China Shanghai SE C.	5,992	0,003	11,958	0,003
DJEuro Stock 50	3,280	0,038	6,555	0,038
Japan Nikkei 225 Average	2,282	0,102	4,563	0,102
Nigeria SP/IFCG	7,786	0,000	15,516	0,000
Portugal PSI 20	1,702	0,182	3,406	0,182
Saudi Arabia SP/IFGC PI	1,211	0,298	2,422	0,298
South Africa FTSE Top40	4,595	0,010	9,178	0,010
UK FTSE 100	10,557	0,000	21,066	0,000
US DJIA	3,484	0,031	6,968	0,031

The result as can be seen from the above table is a clear rejection of the iid hypothesis. Although this test reinforces the BDS tests result, that there are nonlinear relations in all the indexes being studied. The result *per si* does not allow us to assert which is the cause of non-linearity, if the non linearity observed is due to a non linear stochastic process or a deterministic (Chaos) type process. With the next test we try to uncover the source of this nonlinear dependence.

4.7 Engle LM test

This test was proposed by Engle (1982) to detect ARCH disturbances. The idea behind the test is that nonlinear dependence, observed in the series that lead to the rejection of the iid, is transmitted through the variance. This is to say that the variance of t is correlated with the variance of t-p. The test statistic is the LaGrange Multiplier,

$LM=nR^2$ (14),

where n is the number of observation and R^2 is the following regression:

$\mu^2_t = \gamma_0 + \gamma_1\mu\wedge^2_{t-1} + \gamma_2\mu\wedge^2_{t-2} + \ldots + \gamma_q\mu\wedge^2_{t-q} + \upsilon_t$, (15),

where μ^2_t are fitted squared residuals. If the null hypothesis is accepted, this to say there are no ARCH effects, then test is asymptotically distributed: $\chi^2(q)$.

Table 4: Results of the LM test (for full result please refer to the Appendix 8- Section 4.7)

	ARCH LM Test:			
Indices	F-statistic	Probability	Obs*R-squared	Probability
Brazil Bovespa	0,033	0,857	0,033	0,856
Canada SP/TS Index	795,392	0,000	736,434	0,000
China SE Composite	1,508	0,220	1,508	0,219
DJEUROSTOXX50	271,780	0,000	258,415	0,000
Japan Nikkei 225	148,323	0,000	146,675	0,000
Nigeria IFG	111,744	0,000	107,798	0,000
Portugal PSI20	190,755	0,000	181,373	0,000
Saudi Arabia IFGC	170,211	0,000	158,823	0,000
South Africa FTSE Top 40	460,849	0,000	399,678	0,000
UK FTSE 100	67,779	0,000	62,206	0,000
US DJIA	253,837	0,000	249,535	0,000

For all market indices, except for Brazil Bovespa, the null hypothesis is rejected. This means that part of the linearity observed in the series of market indices returns is due to dependences in the variance. In other words, there are ARCH effects in all the market indices and the evidence of strong conditional heteroskedasticity, which is common to most financial markets assets. This result is a strong case for multiplicative dependence, meaning that nonlinearity enters through the variance of the process, which the general form of conditional heteroskedasticity, in Engle 1982). From this test result we cannot conclude on the global market efficiency. But, as already mentioned, second moment dependence is consistent with the Martingale model.

4.8 Technical Analysis/Simulation Strategy

4.8.1 Description of the Methodology

The data used is also from the data stream database. However, there is a significant difference between the two set of series used in this study, the time length considered. In this study we used the data for the shorter series. This is because we wanted to consider the same time length for each index during the simulation period. The data starts in May 12th 2000 and ends at December 29 2006.

4.8.1.1 Trading Simulation Strategy

In any simulation strategy the aim is to outperform the market, the benchmark used in this thesis is the MSCI Global Index. We wanted to find out whether there is momentum in world market indexes and if so, can this fact be used to make profitable investment? We know, at this point that there is non linear dependence and also know nothing can be inferred about global market efficiency hypothesis. The question, now, is to know whether a simple trading strategy can generate profit. A naïve strategy that buys the best performer and sells the poorest performer can generate significant leverage over the buy and hold strategy[95]. If we succeed this would put into question the market efficiency hypothesis. In that sense we constructed a model that at every point in time buys the most valuable stocks indices, "the glamorous indices". The logic, in some way, is in line with Alexander's (1961) simulation. If the stocks index prices goes up above its moving average it is bought if it fells below the moving average is sold (at the closing price of the day). Contrary to Alexander's first study we assume the buy orders are executed at the same day the signal is flagged and at the closing price and the sell executed in the same conditions as the buy[96].

To select the indices first, we determine which indices have outperformed the respective moving average then we ranked them. After this we select the best performers. The number of indices selected is in direct connection with the size of portfolio determined and the number of indices that performed better than the moving averages. For example, if 10 indices have performed better than the moving average and the portfolio size is 20, this means that the entire capital for investment will be allocated to the 10 best indices. If, on the contrary, the portfolio size is say 5, this means that the resource will be allocated to the 5 best performers. This analysis is done on a daily basis. For the equal weighted allocation of resources the amount available for investment is divided evenly to the indices selected. For the value weighted allocation of resources, the amount for investment is divided to the selected indices according to their performance in relationship to the other. That is, for example, if index one as advanced 60% more than the other indices than 60% of resource will be allocated to that index. The rest of the resource is allocated to the

[95] We have not considered the short sells, as there is some restriction regarding short sells in many markets.
[96] Of course, we are perfectly aware of the bias inherent to the use of closing prices instead of the real transaction prices. However this would be an impossible task as it would require the use of high frequency data, prices at every minute, data which is not available for all the market indices. For the purpose of this study this data will suffice.

remaining indices in the same procedure. The allocation is based on each indices performance relative to the rest of the indices.

We tested simple moving averages, weighted moving averages and exponential moving averages (for details on these techniques please refer to the point 2.3.1) for different portfolio sizes: 10, 20, 34 and 40 and different trading days, 1 - 50, 1 - 100 and 1 - 200. For all these combinations we considered the equal and value weighted allocation of resources. The initial amount for investment considered for the simulation is $1.000.000,00. We considered every transaction to involve commission, for every buy we pay a commission for every sell we pay commission. We also considered the minimum amount required for investment to be $10.000,00 (1% of the initial capital) as way to reduce the number of transactions, hence the cost of transactions involved[97]. Whenever an amount of capital is not invested in the market indices it is placed in a bank deposit arning interest rate[98].

4.9 Results of the Simulation Strategy

We report here the results of applying the technical trading strategies to the global index markets data. The idea is that technical analyses capture the information contained in the past prices. The results for the trading strategy are reported in table 5. We report the daily average returns and the corresponding t-statistics[99].

[97] This is the same procedure adopted by Brock, Lakonishock and Lebaron (1992).
[98] We considered the average interest rate provided by Bloomberg.
[99] As in Brock et. al (1992) we used the following statistics: $(\mu_b-\mu_s)/(\delta^2/Nb+\delta^2/Ns)^{(1/2)}$

Table 5: Results for the Simple Moving Average (see appendix 9- Section 4.9 for the full results)

	Simple Moving Average								
Size\Days	50			100			200		
	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s
10	5.400	0,0096	0,0009 45,4863	2.573	0,0127	0,0012 58,2750	1.056	0,0074	0,0009 33,7871
20	11.734	0,0089	0,0009 42,1501	5.518	0,0124	0,0012 56,7760	2.546	0,0072	0,0009 32,8026
34	17.299	0,0088	0,0008 41,4455	8.729	0,0123	0,0012 56,5409	4.482	0,0070	0,0009 32,3102
40	19.008	0,0088	0,0008 41,4636	9.546	0,0122	0,0012 56,2214	5.178	0,0070	0,0009 32,0799

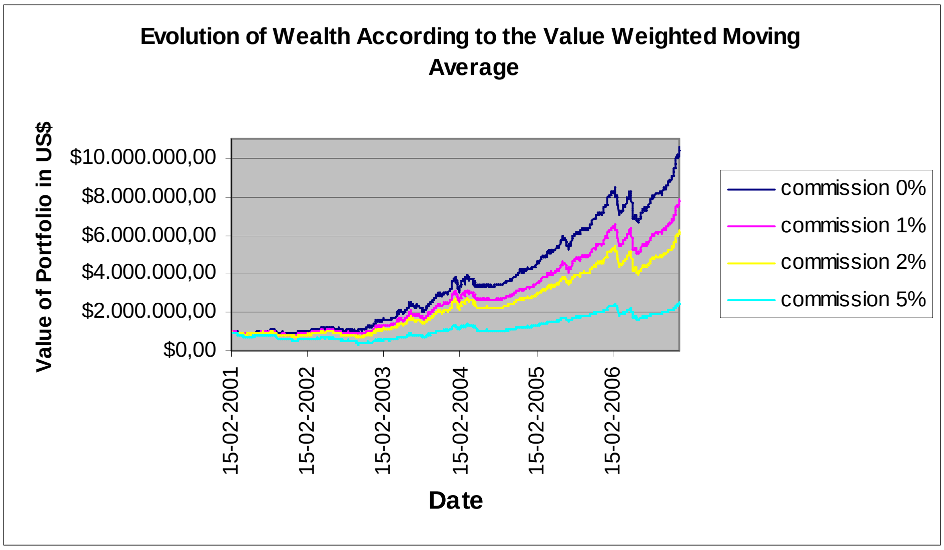
Note: N is the total number transaction (buy+sell); r is daily return and t-s is the t statistics.

Simulation showed predictive power for all the techniques and the time intervals considered and fees considered. For the 50 days time interval, the exponential moving average achieves the best result. For 100 days the best result is achieved with simple moving average. The results for value weighted portfolio are far superior to the equal allocation of resource and this result is not a trade off for risk, as in some cases the standard deviation from the equal allocation are greater than the value weighted resource allocation.

The results are striking. All the strategies are profitable for the 1% and 2% commission and the t-test are highly significant at the 5% significance level. The number of buys is far superior to the number of sells. This is consistent with an upward market trend. This strategy produces result above the buy and hold strategy. The average return of the 50 days simple moving average, portfolio size 10 is 0,0009%, which annual terms amount to 36,88% compared to the -0,6696% obtained with the buy and hold strategy.

The introduction of commission fees reduced considerably the number of transactions and the results of the simulation; nonetheless the results are still positive and significant. The effect of transaction costs can be seen in the bellow graph. The commission is of great importance as it determines which combination size/days is the most profitable. When no commission and 1% fee is considered, the best size for portfolio is 20 indices. This is perhaps due to the fact that an increase in portfolio size does not necessarily mean increasing returns. On the other hand it surely means more transaction costs. This can bee seen by the fact that as the commission fees increase to 2% the best portfolio size is 10 and the worst is 40.

Graph1: The effect of commission fees on the evolution of wealth (for full results in dollar see Appendix 10 - Results in dollars)



The long range moving averages (100 days and 200 days) have a better predictive power for simple and weighted moving averages. The opposite is true for the 50 exponential moving averages are the most profitable of all.

The results of the simulation are similar to many technical analysis studies, that is they favoured the technical analysis approach over the buy and hold strategy. This is in line with the results by Brock et. al (1992), Bessembinder and Chan (1995), Ito (1999), Tian et al.(2004), Kwon et al.(2002) and Loh (2007). These results, however, are contrary to early findings of the 60s, where after commission the results of technical analysis are rendered negative.

4.10 Sharpe Ratio

We performed additional tests to evaluate our simulation strategy against the buy and hold. Comparison of risk and return between the alternate techniques and with the buy and hold strategy. We used the Sharpe (1966) ratio, in order to test whether the results of the previous section are a trade off between risk and reward for bearing fundamental risk. For this analysis we used the Sharpe ratio, this ratio relates the returns and the standard deviation in the following manner:

$S_R = r/\delta$ (16), where r is the return and δ is the standard deviation.

The interpretation is quite simple, the higher the S_R, the higher the mean return and the lower the volatility. The results of this additional profitability test are presented in the table 6. The SR confirms that the result is not a trade off for risk, as the SR is greater than the buy and hold strategy. Although, the average annual standard deviation for the buy and hold strategy is around 16,20% whilst the moving averages were two times higher, the average annual returns is much higher than the buy and hold, five to ten times. This simply means that it is preferred to invest in this portfolio instead of the MSCI Global index.

Table 6: Results of the Sharpe Ratio for 1% commission fee (see Appendix 11 for full result)

	Simple Moving Average			**Weighted Moving Average**			**Exponential Moving Average**		
Size\Days	50	100	200	50	100	200	50	100	200
10	0,0905	0,0905	0,1230	0,0839	0,0917	0,0937	0,0932	0,0977	0,1428
20	0,1003	0,0976	0,1190	0,0861	0,0968	0,0995	0,0922	0,1059	0,1452
34	0,0948	0,0956	0,1247	0,0737	0,0988	0,0963	0,0864	0,1043	0,1443
40	0,0939	0,0985	0,1277	0,0724	0,0959	0,0986	0,0862	0,1084	0,1463
Buy hold	-0,00213	0,00173	0,00756						

4.11 Bootstrap Analysis

The results presented in the previous two sections, the t-test and Sharpe ratio of the previous point 4.9 and 4.10, has at is core the assumption of normality, stationarity and independent distribution. Stock returns are known to be: leptokurtic, asymmetric and conditional heteroskedastic (see point 4.4.1 and 4.7). We used the bootstrap methodology as proposed by Brock et al.(1992), in order to address these problems, because it is robust in accounting for non-normality, autocorrelation, etc. The bootstrap is a non parametric technique which involves large number of iterative computations to estimate the shape of a statistical distribution empirically. It involves drawing with replacement samples of the same size as the original data, in this case the return of the portfolio. The model to be used is a random walk with drift expressed in the following relationship:

$LnP_t = LnP_{t-1} + \varepsilon_t$ (17)

This methodology will be used for the simple moving average technique only. The number of iterations to be considered is 507[100]. This is to test if the technical trading rule captures the some particular stochastic process underlying the portfolio returns. The results for the random walk with drift are reported in the table 7.

Table 7 – Result of the Bootstrap Analysis (for full result see Appendix 4.11 Bootstrap Analysis)

	Simple Moving Average			
Days	50			
Commission (%)	2			
Resource Allocation*	E			
Size	10	20	34	40
R	0,0546%	0,0535%	0,0462%	0,0430%
S	0,01041	0,00964	0,00968	0,00966
t-statistics	0,65730	1,17190	1,39847**	1,31411**
p-value	0,25460	0,12100	0,08080	0,09510
n transactions	5235	11014	16121	17258

Note: *E= Equal Allocation; V=Value Allocation
** significant at 10%

We compared the boostrap result with that of the trade simulation, at 5% significance level, the t-statistics confirms equality of means, only in two out of 13 cases this does not happen. This means that the random walk model does replicate the mean return in 77% of the cases. At 10% significance level , the number of cases not replicated reaches 4 out of 13. These results are similar to the results by Brock et al. (19923) and Kwon and Kish (2000).

[100] According to Efron and Tibshirani (1986), 500 replications is close to the true estimator. Also see Bock et. al (1992).

5 Conclusion

Market efficiency, prices “fully reflect” the available information, has been the concern of many researchers over the years. Traditionally market efficiency was upheld whenever a result of the linear model provided zero correlation on the series returns. In order to test market efficiency we used BDS test, a non linear model, to test for series dependencies, hence market efficiency. The result of the BDS test allowed us to conclude that the global stock market series of returns exhibit dependency in variance, which implies some degree of predictability. We performed the Mcleod-Li test, and the result of this test reinforced the result of the BDS test. We also carried out the Engle’s LM test, which provided us with cause of nonlinearity, the ARCH effect. Although we cannot conclude anything about market efficiency based on this finding, because the volatility dependence is consistent with market efficiency. However, these results are promising as they indicate predictability of indices’ returns.

For the technical trading strategy we build a portfolio model that selects and buys, at any given time, the most profitable indices and sells the less profitable. We tested these strategies with an even and value weighted allocation of resource, different portfolio sizes and commissions fees. The result for the buy and hold strategy is -0,669% daily average return. The result for the technical trading rule, 50 days simple moving average, portfolio size 10 and 1%, is 0,0009% daily average return, which is significantly different from buy and hold strategy. These results are robust even after considering commission fees. The result of technical trading simulation for 1% and 2% commission are all profitable and statiscally significant for all length and portfolio size considered.

The commission fee that played an important part on the studies conducted by Alexander (1961) and Fama and Blume (1966), also palyed an important role in this study. We found that the main determinant for the portfolio size is the commission fee, as the commission fee increases the best result is achieved with the smallest portfolio size.

The result of the bootstrap simulation confirmed the results obtained through the trading simulation. Contrary to the held belief on technical analysis, this result is economically and statistically significant. The reason for the predictability can be traced back to ARCH effect identified by Enlge's LM test.

Therefore, the belief held by some economists that technical analysis is a waste of time may be put in question, because the results strongly support the technical analysis tested in this thesis. These results also suggest that even in an upward market trend active portfolio management can make a difference, which is good news for portfolio manager. In addition to this test we used the Sharpe ratio as to counter against the buy and hold strategy and the effect of risk premium. The Sharpe ratio for the portfolio are superior to that of the buy and hold. Leading us to conclude that this result is not only a trade off to risk, but a better investment than the buy and hold strategy.

We used the bootstrap methodology with the purpose of capturing the stochastic process underlying the portfolio return. The result of the bootstrap conformed to the technical trading strategy. The comparison of the t-test for the portfolio return revealed that the mean returns are statiscally equal, both the unconditional as well as the resample mean. That is to say in general, in 70% at 10% significance level, the random model manages to replicate the trading simulation.

Taking into account the result of the technical trading strategies and result of nonlinear tests, we can assert that the global market is not weak form efficient. Is this to say we have found the money making machine? Hardly. This result can only be replicated under the conditions we mention, using closing prices and considering no difficulties in trading in all these markets. However, in real world, one should be cautious in reading these results, for if we consider: bias induced by using closing price to simulate trade, as pointed out by Amiud and Mendelson (1987b) the use of closing price bias the profitability result upwardly; the liquidity issue in trading in thin markets and the risk premium associated to trading in emerging markets. This can lead us to conclude that part of the result could be due to risk premium or market microstruture associated to dealing in these markets. And these seemingly extraordinary results may in fact be difficult to replicate in real world.

However, this not to say that that the result of this thesis is complete, there is much remain to be done. We must recognise that this thesis holds some limitations, regarding the collection of data.

In real situation, the data used would be a high frequency data not closing prices. The transaction cost, we used arbitrarily the 1% and 2% commission fee with no information on the real transaction cost around the world. We are not familiar with the effect of the transaction of a large amount of indices on the prices of the indices sold or bought (thin trading). This would change the final outcome. There is also the effect of liquidity, particularly serious for small markets. In this case it would both difficult to enter those markets as to leave when necessary.

This work can be enriched with the use of other nonlinearity test, such as the hinich bispectrum. The use of other tools available to technical analysts, as in this thesis we used the most simple and basic widely used strategy, however, the work would benefit with a more real approach using the Moving Average Convergence/Divergence (MACD) - a trend-following momentum indicator that shows the relationship between two moving averages of prices - Relative Strength (RSI) - measures the price of a security against its past performance to determine its internal strength and Parabolic SAR or Parabolic Stop and Reverse. And the bootstrap methodology used could have been tested for the entire set of simulations tested and also the ARCH type process as the return generating mechanism could have been used, instead of just random walk.

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Appendix

Appendix 1- Section 2.4.5 BDS

The BDS is based on correlation integral $Cm(\varepsilon)$ presented by Grassberger and Procacia (1983). Given a time series $\{r_t\}^n_{t=1}=\{r_t:t=1,2,\ldots.n\}$, the correlation integral, $Cm,n(\varepsilon)$, of m dimension (embedding dimension) is given by:

- $C_{m,n}(\varepsilon)=(2/(T_m-T_{m-1}))\sum I_\varepsilon(\|R_t-R_s\|$, (1) where:
- R_t- $=(r_t, r_{t-1}, \ldots.. r_{t-m+1})$;
- Each R_t-is a vector of dimension m and it is called m-history of $\{r_t\}^n_{t=1}$;
- n is the number of observation in the time series;
- m is the embedding dimension
- T_m=n-m+1 is the number of m histories non overlapped that is possible to create from the n observations;
- $I_\varepsilon(\|R_t-R_s\|=\{1$ if $\|R_t-R_s\|<\varepsilon$ and 0 if $\|R_t-R_s\|\geq\varepsilon$ and $\|.\|$ is the non $L\infty$ in $R^m\}$

  ε is a measure of distance of m-dimension vectors. Hsieh (1989) defines ε in terms of multiples of time series' standard deviation: 1,5; 1,25;1,0;0,75 and 0,5.

$C_{m,n}(\varepsilon)$ is a probability estimate of the distance of any pair of m-histories R_t and R_s of the time series $\{r_t\}^n_{t=1}$ being less than ε. An high $C_{m,n}(\varepsilon)$, close to one , means for small value of ε the data are strongly correlated. In the cases where $\{r_t\}$ are independents for $t\neq s$, the joint probability should be equal to the product of individual probabilities. Brock, Deckert, Sheinkman and Le Baron(1991) show that, if the time series is iid then we have $C_{m,n}(\varepsilon)\rightarrow C_{1,n}(\varepsilon)^m$ with probability of 1 as the n increases to infinity, for any given value of m and ε. The BDS test statistics is given by: $W_{m,n}(\varepsilon)=(n[C_{m,n}(\varepsilon)- C_{1,n}(\varepsilon)^m])^{(1/2)}/\sigma_{m,n}(\varepsilon)$, (2) if the iid is true then

$W_{m,n}(\varepsilon)=(n[C_{m,n}(\varepsilon)- C_{1,n}(\varepsilon)^m])^{(1/2)} \approx N(0, \sigma_{m,n}(\varepsilon))$, (3) where

$\sigma_{m,n}(\varepsilon) = \{4[K^m+2 \sum_{j=1}^{m-1}K^{m-j} C^{2j}+(m-1)^2C^{2m}-m^2KC^{2m-2}]\}^{1/2}$ (4)

For Brock et al.(1991) a consistence estimator for $\sigma_{m,n}(\varepsilon)$ replacing C and K for $C_{1,n}(\varepsilon)$ and K_n, respectively, where: $K_n=6\sum_{t<s<q} I\varepsilon(R_t,R_s)I\varepsilon(R_t-R_q)/ T_m(T_m-T_1)(T_m-T_2)$, (5) if iid is true then $W_{m,n}(\varepsilon)$ is N(0,1) asymptotically distributed.

Appendix 2 - Section 4.2.1 NonLinear Test

Table: Result of a single-blind controlled competition among tests for nonlinearity and chaos

		Small Sample		Large Sample	
Test	Null Hypothesis	Sucesses	Failure	Sucesses	Failure
Hinich	Lack of third order	3	2	3 plus ambiguous in 1 case	1 plus ambiguos in 1 case
BDS	Nonlinear dependence Linear process	2	3 plus ambiguous in 1 case	5	0
NEGM	Chaos	5	0	5	0
White	Linearity in mean	4	1	4	1
Kaplan	Linear Process	5	0	5	0

Source: Barnet and Serletis(2000)

Appendix 3 – Section 4.3

Only after this, a nonlinear test statistics can be used. An ARMA type model is of the kind:

A moving average of order q, or in short an MA(q) as: $y_t = \varepsilon_t + \alpha_1 \varepsilon_{t-1} + \ldots + \alpha_q \varepsilon_{t-q}$, (1)

where εt is a white noise process and $y_t = Y_{t-1}$. An autoregressive process of order p, an AR(p) process, is given by: $y_t = \theta_1 y_{t-1} + \theta 2 y_{t-2} + \ldots + \theta_p y_{t-p}$ (2)

An autoregressive moving average, ARMA, is simply a combination of the two relationships above. An ARMA(p,q) model consist of an AR part of order p and an MA part of order q, ARMA(p,q): $y_t = \varepsilon_t + \alpha_1 \varepsilon_{t-1} + \ldots + \alpha_q \varepsilon_{t-q}, + \theta_1 y_{t-1} + \theta 2 y_{t-2} + \ldots + \theta_p y_{t-p}$ (3)

Appendix 4- Section 4.2 Data Stream Market Capitalisation

values in thousands (000)

Market	Type	Capital	CURRENCY
Argentina	TOTMKAR	23.185,00	U$
Australia	TOTMKAU	717.154,00	U$
Austria	TOTMKOE	132.599,00	U$
Belgium	TOTMKBG	270.873,00	U$
Brazil	TOTMKBR	421.763,00	U$
Canada	TOTMKCN	1.211.265,00	U$
Chile	TOTMKCL	112.740,00	U$
China	TOTMKCH	156.450,00	U$
Columbia	TOTMKCB	41.176,00	U$
Korea	TOTMKCO	#N/A	NA
Denmark	TOTMKDK	159.218,00	U$
Finland	TOTMKFN	198.016,00	U$
France	TOTMKFR	1.676.982,00	U$
Germany	TOTMKBD	1.210.461,00	U$
Greece	TOTMKGR	120.764,00	U$
Hong Kong	TOTMKHK	777.920,00	U$
India	TOTMKIN	389.416,00	U$
Indonesia	TOTMKID	71.042,00	U$
Ireland	TOTMKIR	109.056,00	U$
Italy	TOTMKIT	782.819,00	U$
Japan	TOTMKJP	4.247.536,00	U$
Malaysia	TOTMKMY	141.485,00	U$
Mexico	TOTMKMX	234.167,00	U$
Netherlands	TOTMKNL	540.458,00	U$
New Zealand	TOTMKNZ	38.398,00	U$
Norway	TOTMKNW	179.202,00	U$
Peru	TOTMKPE	19.784,00	U$
Philippines	TOTMKPH	40.685,00	U$
Poland	TOTMKPO	76.364,00	U$
Portugal	TOTMKPT	70.283,00	U$
Singapore	TOTMKSG	178.961,00	U$
South Africa	TOTMKSA	274.720,00	U$
Spain	TOTMKES	650.630,00	U$
Sweden	TOTMKSD	359.911,00	U$
Switzerland	TOTMKSW	935.582,00	U$
Taiwan	TOTMKTA	330.656,00	U$
Thailand	TOTMKTH	92.627,00	U$
Turkey	TOTMKTK	125.098,00	U$
United Kingdom	TOTMKUK	3.009.420,00	U$
United States	TOTMKUS	14.090.610,00	U$

Appendix 5 - Section 4.4.1 to Table 1- Table of Descriptive Statistics

	Appendix 4.4.1 -Table 1 of the descriptive statistics									
Indices	**Obs.**	**Mean**	**Median**	**Max.**	**Min.**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera**	**Probability**
Series: RT_ARGENTINAMERVAL	3499	0,014	0,040	17,790	-33,650	2,411	-1,060	20,176	43665,63	0.000000
Series: RT_CHILEGENERALIGPA	5215	0,055	0,000	10,200	-12,260	1,128	-0,132	11,529	15820,73	0.000000
Series: RT_PERULIMASEGENERALIGBL	4172	0,105	0,058	9,722	-12,061	1,589	0,014	9,387	7.091	0.000000
Series: RT_MEXICOIPCBOLSA	4954	0,080	0,083	15,290	-21,797	1,941	-0,527	14,988	29891,78	0.000000
Series: RT_BRAZILBOVESPA	6188	0,056	0,022	69,316	-69,525	4,242	0,861	58,751	802145,4	0.000000
Series: RT_CANADASPINDEX	9912	0,024	0,031	8,909	-11,891	0,918	-0,770	14,297	53684,79	0.000000
Series: RT_USADJIA	14608	0,027	0,006	9,666	-25,632	0,895	-1,694	54,843	1642872	0.000000
Series: RT_USASP500	11218	0,026	0,010	8,709	-22,833	0,931	-1,369	40,124	647677,8	0.000000
Series: RT_USNASDAQ100	6259	0,044	0,055	17,203	-16,341	1,698	-0,069	10,780	15790,55	0.000000
Series: RT_KENIANAIROBISE	4426	0,017	0,000	48,606	-49,330	1,736	0,273	36,728	24471917	0.000000
Series: RT_MOROCCOSECFG25	4956	0,059	0,026	15,252	-10,751	1,156	0,413	21,696	72324,63	0.000000
Series: RT_NIGERIAIFCG	3000	0,076	0,036	10,277	-10,439	1,103	-0,057	12,329	10880,33	0.000000
Series: RT_SOUTHAFRICAFTSETOP4	3000	0,031	0,066	8,776	-15,095	1,526	-0,692	10,346	6.985.588	0.000000
Series: RT_CHINASHANGHAISECOMP	4172	0,063	0,001	71,230	-38,957	2,689	4,630	143,458	3.444.351	0.000000
Series: RT_HONGKONGHANGSENGIND	10957	0,044	0,000	17,270	-41,768	1,849	-1,669	44,241	781584,8	0.000000
Series: RT_INDIABSENATIONAL200	4171	0,039	0,000	17,964	-13,068	1,705	-0,168	12,548	15861,58	0.000000
Series: RT_JANIKKEI225STOCK	13021	0,035	0,000	13,313	-19,262	1,263	-0,338	16,148	94030,29	0.000000
Series: RT_POLANDWARSAWGENERAL	4098	0,068	0,023	15,521	-17,395	2,137	-0,158	9,581	7.413	0.000000
Series: RT_CZECHPRAGUESEPX	3322	0,025	0,000	7,182	-6,920	1,336	-0,252	5,383	821	0.000000
Series: RT_RUSSIARTSINDEX	2955	0,100	0,043	15,557	-21,103	2,789	-0,485	9,749	5.725	0.000000
Series: RT_ISRAELTA100	5136	0,042	0,054	10,353	-11,227	1,734	-0,383	7,258	4.005	0.000000
Series: RT_KUWAITALSHALLGENERA	1730	0,092	0,037	51,339	-49,393	2,160	0,746	352,075	8783740	0.000000
Series: RT_SAUDIARABIASPIFCG	2347	0,056	0,000	16,009	-13,211	1,402	-0,823	24,583	45818,1	0.000000
Series: RT_NETHERLANDAMEXINDEX	6259	0,045	0,077	10,408	-11,325	1,290	-0,291	9,030	9.572	0.000000
Series: RT_DENMARKOMXC20	4454	0,036	0,049	6,660	-9,007	1,112	-0,349	6,253	2.054	0.000000
Series: RT_FINLANDOMXHELSINKI25	4868	0,032	0,066	7,592	-9,190	1,460	-0,273	6,198	2.135	0.000000
Series: RT_IRELANDSEOVERALLI	6257	0,057	0,048	7,328	-14,116	1,140	-0,444	12,214	22337,53	0.000000
Series: RT_LUXEMBOURGSEGENERAL	2084	0,028	0,037	9,446	-10,944	1,188	-0,409	10,690	5.194	0.000000
Series: RT_SWEDENOMXSTOCKHOLM3	5476	0,048	0,056	10,898	-9,594	1,481	-0,090	6,970	3.603	0.000000
Series: RT_SWISSMARKETPRICE	4825	0,041	0,030	7,100	-9,542	1,143	-0,233	8,089	5.250	0.000000
Series: RT_KOREASEKOSPI200	4432	0,006	0,000	40,547	-40,547	4,863	-0,002	23,339	76392,38	0.000000
Series: RT_AUSTRALIASPASX200PI	3805	0,033	0,042	7,369	-7,013	1,065	-0,173	5,838	1.296	0.000000
Series: RT_INDONESIAJAKARTASEC	6194	0,011	0,000	38,878	-38,566	2,375	-0,821	55,564	713775,9	0.000000
Series: RT_MALAYSIAKLCICOMPOSI	7042	0,017	0,006	23,408	-37,010	1,686	-1,414	61,160	994858,4	0.000000
Series: RT_NEWZEALANDNZXALLPI	4432	0,015	0,032	9,057	-12,313	1,109	-0,458	10,927	11760,56	0.000000
Series: RT_PHILIPPINESEI	5476	0,039	0,000	21,266	-15,423	1,972	0,350	13,206	23877,84	0.000000
Series: RT_SINGAPOREALL	5476	0,028	0,039	13,573	-9,599	1,203	-0,023	13,965	27430,88	0.000000
Series: RT_TAIWANSE100	3000	0,011	0,000	13,287	-11,664	1,710	-0,039	7,335	2.350	0.000000
Series: RT_DJEUROSTOXX50	5217	0,033	0,067	7,572	-10,144	1,213	-0,282	7,655	4.780	0.000000
Series: RT_FRANCECAC40PRI	5081	0,030	0,050	9,059	-10,287	1,300	-0,280	7,369	4.107	0.000000
Series: RT_GERMANYDAX30PERFOR	10956	0,033	0,022	9,332	-13,058	1,227	-0,203	8,937	16.167	0.000000
Series: RT_GREECEFTSEATHEX20	2418	0,040	0,048	8,248	-9,811	1,784	0,043	6,240	1.058	0.000000
Series: RT_TURKEYISENATIONAL100	4954	0,027	0,003	22,475	-28,040	3,272	-0,187	8,071	5.338	0.000000
Series: RT_ITALYSPMIBINDEXPRIC	2347	0,030	0,046	7,530	-6,986	1,346	-0,125	5,573	6.538	0.000000
Series: RT_PORTUGALPSI20	3651	0,035	0,036	5,926	-8,243	1,066	-0,276	7,011	2.494	0.000000
Series: RT_UKFTSE100	7543	0,035	0,023	12,673	-17,600	1,140	-0,523	23,114	127500	0.000000
Series: RT_THAILANDBANGKOKSET50	2967	-0,038	0,000	231,959	-230,221	10,576	0,073	450,591	24766707	0.000000
Series: RT_SPAINIBEX35	5214	0,037	0,052	9,324	-11,254	1,308	-0,270	7,899	5.277	0.000000
Series: RT_NORWAYOSLOSEOBX	5215	0,041	0,054	11,140	-25,430	1,439	-1,428	27,584	133096,8	0.000000
Series: RT_BAHRAINDOWJONES	1825	0,035	0,000	4,048	-3,431	0,553	0,384	11,058	4.983	0.000000

nº indices	**53**
Max	**14608**
Min	**1730**

Appendix 5-Section 4.5 to Table 2 – Table 2 BDS Test Results

Appendix 4.5 to Table 2. Brock Decker and Shenkem Test (BDS Test)

	Dimension					BDS Statistic					Std, Error					z-Statistic				
Indices/Dimension	2	3	4	5	6	2	3	4	5	6	2	3	4	5	6	2	3	4	5	6
Argentina Merval	2	3	4	5	6	0,02	0,04	0,06	0,07	0,07	0,00	0,00	0,00	0,00	0,00	13,03	16,98	19,35	21,16	22,76
Australia SP/ASX 200	2	3	4	5	6	0,01	0,01	0,02	0,02	0,02	0,00	0,00	0,00	0,00	0,00	56,83	64,35	72,44	80,59	90,24
Baharain Dow Jones	2	3	4	5	6	0,01	0,02	0,03	0,04	0,04	0,00	0,00	0,01	0,01	0,01	41,58	54,84	63,31	66,53	75,34
Brazil Bovespa	2	3	4	5	6	0,02	0,05	0,07	0,08	0,09	0,00	0,00	0,00	0,00	0,00	18,79	23,89	28,25	32,35	36,62
Canada SP/TX	2	3	4	5	6	0,02	0,04	0,06	0,07	0,07	0,00	0,00	0,00	0,00	0,00	22,10	28,14	32,05	35,61	39,02
Chile General IGPA	2	3	4	5	6	0,02	0,04	0,05	0,06	0,06	0,00	0,00	0,00	0,00	0,00	16,88	19,01	21,32	23,67	26,12
China Shanghai SE Com	2	3	4	5	6	0,04	0,08	0,10	0,12	0,12	0,00	0,00	0,00	0,00	0,00	22,67	27,54	31,16	34,07	37,07
Czeck Prague SE	2	3	4	5	6	0,02	0,03	0,05	0,05	0,06	0,00	0,00	0,00	0,00	0,00	11,56	14,64	16,65	18,27	20,14
Denmar OMXC	2	3	4	5	6	0,01	0,03	0,03	0,04	0,04	0,00	0,00	0,00	0,00	0,00	10,59	12,57	13,92	15,22	16,44
Djeurostoxx50	2	3	4	5	6	0,02	0,04	0,05	0,06	0,06	0,00	0,00	0,00	0,00	0,00	14,91	19,65	23,02	25,19	27,31
Finland OMXHI	2	3	4	5	6	0,02	0,04	0,05	0,06	0,06	0,00	0,00	0,00	0,00	0,00	16,07	19,72	22,04	24,34	26,44
France CAC 40	2	3	4	5	6	0,01	0,03	0,04	0,04	0,04	0,00	0,00	0,00	0,00	0,00	10,40	13,79	16,22	17,66	18,81
Germany DAX 30	2	3	4	5	6	0,02	0,03	0,05	0,05	0,06	0,00	0,00	0,00	0,00	0,00	19,93	26,19	30,74	34,18	37,71
Greece Athens SE 20	2	3	4	5	6	0,02	0,04	0,06	0,07	0,07	0,00	0,00	0,00	0,00	0,00	11,27	14,84	16,82	18,26	20,08
Hong Kong Hang Seng	2	3	4	5	6	0,03	0,06	0,08	0,09	0,10	0,00	0,00	0,00	0,00	0,00	27,34	34,84	40,38	45,28	50,49
India Bse National 200	2	3	4	5	6	0,02	0,05	0,06	0,07	0,07	0,00	0,00	0,00	0,00	0,00	16,89	19,64	21,37	22,63	24,16
Indonesia Jakarta SE Comp	2	3	4	5	6	0,03	0,07	0,09	0,10	0,10	0,00	0,00	0,00	0,00	0,00	24,90	30,46	33,43	35,78	38,44
Ireland Overall SE Index	2	3	4	5	6	0,01	0,02	0,03	0,03	0,03	0,00	0,00	0,00	0,00	0,00	96,89	10,93	11,84	12,27	14,03
Israel TA	2	3	4	5	6	0,02	0,03	0,05	0,06	0,06	0,00	0,00	0,00	0,00	0,00	12,51	17,16	20,99	23,48	26,22
Italy SP/MIB PI	2	3	4	5	6	0,02	0,04	0,06	0,07	0,08	0,00	0,00	0,00	0,00	0,00	94,40	14,14	17,96	20,77	23,52
Japan Nikkei225	2	3	4	5	6	0,02	0,04	0,06	0,07	0,07	0,00	0,00	0,00	0,00	0,00	22,37	31,02	36,65	41,71	46,38
Kenia nairobi se	2	3	4	5	6	0,03	0,06	0,07	0,08	0,08	0,00	0,00	0,00	0,00	0,00	19,96	22,01	23,11	23,55	24,54
Korea se kospi 200	2	3	4	5	6	0,02	0,04	0,07	0,08	0,08	0,00	0,00	0,01	0,01	0,01	88,81	10,27	11,63	11,99	12,21
Kuwaitallsharege	2	3	4	5	6	0,04	0,07	0,09	0,10	0,11	0,00	0,00	0,01	0,01	0,01	15,65	17,05	18,42	19,67	21,02
Luxembourg SE	2	3	4	5	6	0,01	0,02	0,03	0,03	0,03	0,00	0,00	0,00	0,00	0,00	66,19	76,60	83,72	93,08	10,21
Malaysia KLCI com	2	3	4	5	6	0,03	0,06	0,08	0,09	0,10	0,00	0,00	0,00	0,00	0,00	26,19	32,26	35,98	39,19	42,42
Mexico IPCB	2	3	4	5	6	0,02	0,04	0,06	0,06	0,07	0,00	0,00	0,00	0,00	0,00	16,28	19,71	22,26	24,50	26,48
Morocco SE CFG	2	3	4	5	6	0,03	0,05	0,06	0,07	0,08	0,00	0,00	0,00	0,00	0,00	19,86	21,16	21,71	24,04	26,29
Netherland AMEX ind	2	3	4	5	6	0,02	0,04	0,05	0,06	0,06	0,00	0,00	0,00	0,00	0,00	16,80	20,81	23,91	26,53	28,75
New Zealand NZXALLl	2	3	4	5	6	0,01	0,02	0,03	0,04	0,04	0,00	0,00	0,00	0,00	0,00	96,30	12,39	14,13	15,71	16,98
Nigeria IFCG	2	3	4	5	6	0,03	0,06	0,07	0,08	0,09	0,00	0,00	0,00	0,00	0,00	16,69	20,00	22,22	23,92	25,85
Norway Oslo OBX	2	3	4	5	6	0,02	0,03	0,05	0,05	0,05	0,00	0,00	0,00	0,00	0,00	14,33	17,98	19,87	20,80	21,95
Peu Lima SE General	2	3	4	5	6	0,04	0,07	0,09	0,11	0,12	0,00	0,00	0,00	0,00	0,00	21,79	26,50	29,63	33,19	37,02
Philippine SEI	2	3	4	5	6	0,03	0,05	0,07	0,08	0,08	0,00	0,00	0,00	0,00	0,00	19,85	24,16	27,11	29,84	33,05
Poland Warsaw GI	2	3	4	5	6	0,02	0,03	0,05	0,05	0,06	0,00	0,00	0,00	0,00	0,00	11,33	13,65	15,84	17,42	18,70
Portugal PSI 20	2	3	4	5	6	0,02	0,04	0,05	0,06	0,06	0,00	0,00	0,00	0,00	0,00	13,92	16,79	18,61	20,10	21,54
Russia RTSI	2	3	4	5	6	0,03	0,06	0,08	0,10	0,10	0,00	0,00	0,00	0,00	0,00	17,01	21,08	23,73	26,09	28,80
Saudi Arabia SP/IFCG	2	3	4	5	6	0,02	0,04	0,04	0,05	0,06	0,00	0,00	0,01	0,01	0,01	76,17	83,40	84,77	87,99	10,83
Singapore ALL	2	3	4	5	6	0,02	0,05	0,06	0,07	0,07	0,00	0,00	0,00	0,00	0,00	19,03	24,08	27,20	29,52	31,94
South Africa FTSE40	2	3	4	5	6	0,02	0,04	0,05	0,06	0,07	0,00	0,00	0,00	0,00	0,00	11,11	15,33	17,56	19,61	21,36
Spain IBEX 35	2	3	4	5	6	0,02	0,03	0,05	0,05	0,05	0,00	0,00	0,00	0,00	0,00	14,32	17,47	20,46	22,76	24,72
Sweden Stock 30	2	3	4	5	6	0,02	0,04	0,05	0,06	0,06	0,00	0,00	0,00	0,00	0,00	17,58	20,76	23,99	26,50	28,73
Swiss Market I	2	3	4	5	6	0,01	0,03	0,04	0,04	0,04	0,00	0,00	0,00	0,00	0,00	12,39	14,80	17,18	18,65	19,77
Taiwan SE100	2	3	4	5	6	0,01	0,02	0,04	0,04	0,05	0,00	0,00	0,00	0,00	0,00	60,39	92,56	11,40	13,25	14,90
Thailand BKSET	2	3	4	5	6	0,03	0,06	0,08	0,09	0,09	0,00	0,00	0,00	0,00	0,00	15,70	19,44	22,21	24,24	26,73
Turkey ISE National	2	3	4	5	6	0,02	0,05	0,07	0,07	0,08	0,00	0,00	0,00	0,00	0,00	18,80	23,79	26,63	28,86	31,36
UK FTSE 100	2	3	4	5	6	0,04	0,09	0,12	0,15	0,16	0,00	0,00	0,00	0,00	0,00	32,06	41,79	49,31	56,52	64,29
US DJIA*	2	3	4	5	6	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	-0,01	-0,01	-0,01	-0,01	-0,01
US Nasdaq 100	2	3	4	5	6	0,02	0,06	0,08	0,09	0,10	0,00	0,00	0,00	0,00	0,00	20,10	28,00	32,42	36,64	40,87
US SP 500	2	3	4	5	6	0,02	0,03	0,05	0,05	0,06	0,00	0,00	0,00	0,00	0,00	17,60	23,63	27,72	31,67	36,12

*The probabilities not represented in the table as they are all zero, except for the US DJIA which are 0,99 for all the dimensions.

Appendix 7- Section 4.6 to Mcleod-Li Test Result

	Appendix 4.6 to Mcleod-Li Test Result				
Indices	F-statistic	Probability		Obs*R-squared	Probability
Argentina Merval Index	2,201	0,111		4,403	0,111
Australia SP/ASX 200	4,209	0,015		8,407	0,015
Baharain Dow Jones	2,006	0,135		4,014	0,134
Brazil Bovespa	3,905	0,020		7,805	0,020
Canada SP Index	4,959	0,007		9,913	0,007
Chile General IGPA	4,737	0,009		9,466	0,009
China Shanghai SE Composite	5,992	0,003		11,958	0,003
Czech Republic Prague SE PX	1,474	0,229		2,949	0,229
Denmark OMX 20	13,768	0,000		27,386	0,000
DJEuro Stock 50	3,280	0,038		6,555	0,038
Finland OMX Helsinki 25	15,322	0,000		30,471	0,000
France CAC 40	3,053	0,047		6,103	0,047
Germany DAX 30	6,866	0,001		13,718	0,001
Greece ATHEX 20	21,225	0,000		41,768	0,000
Hong Kong Hang Seng Index	7,995	0,000		15,970	0,000
India BSE 200 National	1,083	0,339		2,167	0,338
Indonesia Jakarta SEC	6,541	0,001		13,065	0,001
Ireland SE Overall	0,166	0,847	*	0,332	0,847
Israel TA 100	0,869	0,419		1,739	0,419
Italy SP MIB Index	0,161	0,851	*	0,322	0,851
Japan Nikkei 225 Average	2,282	0,102		4,563	0,102
Kenina Nairobi SE	7,786	0,000		15,516	0,000
Korea Kospi 200	130,168	0,000		246,050	0,000
Kwait All Share General	208,217	0,000		336,110	0,000
Louxembourg SE General	2,130	0,119		4,260	0,119
Malaysia KLCI	3,743	0,024		7,482	0,024
Mexico IPC Bolsa	2,779	0,062		5,557	0,062
Morocco SECFG25	9,971	0,000		19,182	0,000
Netherland AEX	1,860	0,156		3,719	0,156
New Zeland All Share PI	2,724	0,066		5,445	0,066
Nigeria SP/IFCG	7,786	0,000		15,516	0,000
Norway Oslo SE	13,382	0,000		26,643	0,000
Peru Lima SE General	2,963	0,052		5,925	0,052
Philipines SE I	0,560	0,571	*	1,120	0,571
Poland Warsaw Index 20	3,262	0,038		6,212	0,045
Portugal PSI 20	1,702	0,182		3,406	0,182
Russia RTS Index	0,458	0,633	*	0,917	0,632
Saudi Arabia SP/IFGC PI	1,211	0,298		2,422	0,298
Singapore All Share	1,002	0,367		2,004	0,367
South Africa FTSE Top40	4,595	0,010		9,178	0,010
Spain IBEX 35	1,702	0,182		3,406	0,182
Sweden OMX Stockholm	13,783	0,000		27,442	0,000
Swiss Market PI	2,593	0,075		5,184	0,075
Taiwan SE 100	1,854	0,157		3,707	0,157
Thailand Bangkok SET 50	304,377	0,000		505,540	0,000
Turkey ISE National 100	0,946	0,388		1,893	0,388
UK FTSE 100	10,557	0,000		21,066	0,000
US DJIA	3,484	0,031		6,968	0,031
US SP500	26,678	0,000		53,117	0,000
USA NASDAQ 100	3,183	0,042		6,362	0,042

* value that accepts H0

Appendix 8- Section 4.7 to Table 4 – Engle's LM Test Result

	Appendix 4.7 to Table 4 – Engle's LM ARCH Test Result:				
Indices	F-statistic	Probability		Obs*R-squared	Probability
Argentina Merval	13,628	0,000		13,582	0,000
Australia SP/AX	79,775	0,000		78,176	0,000
Baharain Dow Jones	24,503	0,000		24,205	0,000
Brazil Bovespa	0,033	0,857	*	0,033	0,856
Canada SP/TS Index	795,392	0,000		736,434	0,000
Chile General IGPA	66,255	0,000		65,448	0,000
China SE Composite	1,508	0,220		1,508	0,219
Czech Prague SE	89,595	0,000		87,292	0,000
Denmark OMXC	235,477	0,000		223,746	0,000
DJEUROSTOXX50	271,780	0,000		258,415	0,000
Finland OMX Helsinki 25	253,941	0,000		241,443	0,000
France CAC 40	133,909	0,000		130,520	0,000
Germany DAX 30	334,593	0,000		324,734	0,000
Greece Athens FTSE	101,770	0,000		97,736	0,000
Hong Kong Hang Seng	47,666	0,000		47,468	0,000
India BSE National 200	336,228	0,000		311,274	0,000
Indonesia Jakarta SE Comp	345,761	0,000		327,575	0,000
Irish Overal SE	230,297	0,000		222,187	0,000
Israel TA 100	157,699	0,000		153,058	0,000
Italy SP MIB Index	159,336	0,000		149,322	0,000
Japan Nikkei 225	148,323	0,000		146,675	0,000
Kenya Nairobi Residuals Squared	814,878	0,000		688,415	0,000
Korea Kospi 200	11,632	0,001		11,606	0,001
Kwait All Share General	202,284	0,000		181,273	0,000
Lima SE General	188,978	0,000		180,868	0,000
Luxembourg SE General	88,999	0,000		85,429	0,000
Malaysia KLCI	244,130	0,000		236,012	0,000
Mexico IPC Bolsa	259,641	0,000		246,801	0,000
Moroccon SE 25 CGF	344,855	0,000		322,538	0,000
Netherland AEX	769,193	0,000		685,193	0,000
New Zealand ALL Share	222,051	0,000		211,545	0,000
Nigeria IFG	111,744	0,000		107,798	0,000
Norway Oslo OBX	320,279	0,000		301,853	0,000
Philipines SE	244,284	0,000		233,930	0,000
Poland Warsaw 20	156,771	0,000		149,772	0,000
Portugal PSI20	190,755	0,000		181,373	0,000
Russia RTS Index	290,536	0,000		264,675	0,000
Saudi Arabia IFGC	170,211	0,000		158,823	0,000
Singapore All Share	226,878	0,000		217,926	0,000
South Africa FTSE Top 40	460,849	0,000		399,678	0,000
Spain IBEX 35	142,551	0,000		138,807	0,000
Sweden Stockholm 30	292,806	0,000		278,038	0,000
Swiss Market price Index	187,629	0,000		180,677	0,000
Taiwan 100	251,913	0,000		232,536	0,000
Thailand Bangkok SET 50	358,797	0,000		320,270	0,000
Turkey ISE National 100	491,226	0,000		447,059	0,000
UK FTSE 100	67,779	0,000		62,206	0,000
US DJIA	253,837	0,000		249,535	0,000
US NASDAQ	454,681	0,000		424,009	0,000
US SP500	158,741	0,000		156,554	0,000

* Index that does not accept ARCH effect.

Appendix 9- Section 4.9 to Table 5- Result for the Technical Trading Strategy

0% Commission fee - Equal weighted Allocation of resource

	Simple Moving Average									Weighted Moving Average								
Size\Days	50			100			200			50			100			200		
	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s
		0,0091	0,0013		0,0124	0,0014		0,0072	0,0010		0,0089	0,0013		0,0114	0,0014		0,0131	0,0015
10	5.554		42,441	2.568		56,283	1.073		31,577	7.468		41,422	3.754		51,816	1.628		57,632
		0,0084	0,0013		0,0121	0,0014		0,0069	0,0010		0,0083	0,0013		0,0108	0,0014		0,0127	0,0015
20	12.345		39,083	5.804		54,879	2.688		30,416	15.484		38,899	8.224		49,289	4.203		56,066
		0,0082	0,0013		0,0120	0,0014		0,0068	0,0010		0,0083	0,0013		0,0107	0,0014		0,0126	0,0015
34	18.893		38,524	9.177		54,365	4.707		29,845	23.022		38,766	13.355		48,879	6.638		55,918
		0,0082	0,0013		0,0119	0,0015		0,0067	0,0010		0,0083	0,0012		0,0108	0,0014		0,0126	0,0015
40	20.701		38,235	10.158		54,325	5.412		29,729	24.779		38,807	15.086		48,941	7.465		55,745

Exponential Moving Average								
50			100			200		
N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s
	0,0110	0,0015		0,0116	0,0015		0,0066	0,0011
5.216		51,300	2.793		52,244	989		28,997
	0,0106	0,0015		0,0111	0,0015		0,0063	0,0011
11.323		49,371	6.378		50,269	2.985		27,820
	0,0105	0,0014		0,0109	0,0015		0,0062	0,0011
17.653		49,034	10.008		49,763	5.015		27,464
	0,0105	0,0014		0,0109	0,0015		0,0062	0,0011
19.708		48,972	10.635		49,460	5.745		27,346

1% Commission fee - Equal weighted Allocation of resource

	Simple Moving Average									Weighted Moving Average								
Size\Days	50			100			200			50			100			200		
	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s
		0,0096	0,0009		0,0127	0,0012		0,0074	0,0009		0,0095	0,0008		0,0118	0,0011		0,0134	0,0013
10	5.400		46,101	2.573		58,275	1.056		33,787	7.173		45,455	3.697		54,200	1.572		61,151
		0,0089	0,0009		0,0124	0,0012		0,0072	0,0009		0,0091	0,0008		0,0112	0,0011		0,0130	0,0013
20	11.734		42,715	5.518		56,776	2.546		32,803	14.630		43,633	7.943		51,523	4.081		59,625
		0,0088	0,0008		0,0123	0,0012		0,0070	0,0009		0,0090	0,0007		0,0112	0,0011		0,0130	0,0013
34	17.299		42,000	8.729		56,541	4.482		32,310	20.649		43,062	12.802		51,335	6.230		59,864
		0,0088	0,0008		0,0122	0,0012		0,0070	0,0009		0,0090	0,0007		0,0111	0,0011		0,0130	0,0013
40	19.008		42,018	9.546		56,221	5.178		32,080	22.460		43,319	14.016		51,021	6.979		59,549

Cont. 1 Appendix 9- Section 4.9 to Table 5- Result for the Technical Trading Strategy

Exponential Moving Average								
50			100			200		
N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s
	0,0115	0,0011		0,0120	0,0012		0,0068	0,0010
5.101		54,997	2.693		54,861	1.150		30,913
	0,0111	0,0010		0,0116	0,0012		0,0065	0,0009
10.667		53,346	6.085		53,179	2.976		29,888
	0,0111	0,0010		0,0116	0,0012		0,0064	0,0009
16.231		53,101	9.206		53,160	4.719		29,394
	0,0110	0,0010		0,0114	0,0012		0,0064	0,0009
17.819		52,790	10.197		52,352	5.521		29,264

2% Commission fee - Equal weighted Allocation of resource

	Simple Moving Average									Weighted Moving Average								
Size\Days	50			100			200			50			100			200		
	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s
		0,0104	0,0005		0,0132	0,0009		0,0076	0,0008		0,0105	0,0394%		0,0123	0,0008		0,0139	0,0010
10	5.235		50,273	2.453		61,332	1.004		34,972	6.991		50,582	3.585		56,959	1.520		63,923
		0,0097	0,0005		0,0128	0,0010		0,0074	0,0008		0,0101	0,0359%		0,0118	0,0008		0,0135	0,0010
20	11.014		46,706	5.361		59,312	2.615		34,086	13.557		49,099	7.471		54,877	3.832		62,477
		0,0097	0,0005		0,0128	0,0009		0,0073	0,0008		0,0101	0,000		0,0118	0,0008		0,0135	0,0010
34	16.121		46,892	7.962		59,476	4.418		33,798	18.964		49,117	11.844		54,615	6.022		62,491
		0,0097	0,0004		0,0126	0,0009		0,0073	0,0008		0,0101	0,0228%		0,0118	0,0007		0,0134	0,0010
40	17.258		46,778	9.022		58,654	5.035		33,889	20.344		49,047	13.063		54,893	6.565		62,383

Exponential Moving Average								
50			100			200		
N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s
	0,0124	0,0007		0,0127	0,0010		0,0070	0,0008
5.004		59,838	2.716		58,765	1.153		32,297
	0,0120	0,0006		0,0122	0,0009		0,0068	0,0008
9.992		57,879	5.841		56,574	2.790		31,281
	0,0119	0,0006		0,0121	0,0009		0,0067	0,0008
15.019		57,536	8.649		56,298	4.543		31,001
	0,0119	0,0006		0,0121	0,0009		0,0067	0,0008
16.472		57,600	9.178		56,075	5.386		30,880

Cont. 2 Appendix 9- Section 4.9 to Table 5- Result for the Technical Trading Strategy

0% Commission fee- Value Weighted allocation of resource

	Simple Moving Average									Weighted Moving Average								
Size\Days	50			100			200			50			100			200		
	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s
		0,0104	0,0013		0,0129	0,0015		0,0084	0,0010		0,0100	0,0013		0,0119	0,0014		0,0141	0,0015
10	4.912		48,387	2.212		58,106	871		36,568	6.641		46,649	3.303		53,820	1.251		61,516
		0,0099	0,0013		0,0126	0,0015		0,0081	0,0010		0,0096	0,0012		0,0114	0,0014		0,0138	0,0016
20	9.718		46,252	4.380		57,132	1.833		35,626	12.517		45,089	6.722		51,895	2.731		61,002
		0,0098	0,0013		0,0125	0,0015		0,0080	0,0011		0,0096	0,0012		0,0113	0,0014		0,0138	0,0016
34	14.074		45,663	6.247		56,717	2.670		35,320	17.118		44,970	9.875		51,584	3.751		61,124
		0,0098	0,0013		0,0125	0,0015		0,0080	0,0011		0,0096	0,0012		0,0113	0,0014		0,0138	0,0016
40	14.983		45,727	6.896		56,611	2.950		35,247	18.173		44,854	10.805		51,556	4.136		61,019

Exponential Moving Average								
50			100			200		
N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s
	0,0118	0,0014		0,0125	0,0015		0,0077	0,0011
4.490		54,862	2.279		56,617	904		33,659
	0,0114	0,0014		0,0121	0,0015		0,0075	0,0011
8.833		53,409	4.559		55,037	2.033		33,027
	0,0114	0,0014		0,0120	0,0016		0,0074	0,0011
12.913		53,201	6.353		54,633	2.943		32,801
	0,0114	0,0014		0,0120	0,0016		0,0074	0,0011
14.131		53,100	6.919		54,474	3.264		32,766

1% Commission fee- Value Weighted allocation of resource

	Simple Moving Average									Weighted Moving Average								
Size\Days	50			100			200			50			100			200		
	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s
		0,0108	0,0009		0,0132	0,0013		0,0085	0,0009		0,0106	0,0008		0,0122	0,0012		0,0144	0,0014
10	4.668		51,829	2.198		60,154	853		38,688	6.396		50,776	3.172		56,000	1.236		65,341
		0,0103	0,0009		0,0129	0,0013		0,0082	0,0009		0,0104	0,0008		0,0118	0,0012		0,0142	0,0014
20	9.110		49,215	4.215		59,106	1.742		37,743	11.675		49,597	6.247		54,146	2.670		64,917
		0,0102	0,0009		0,0128	0,0013		0,0082	0,0009		0,0103	0,0007		0,0117	0,0012		0,0142	0,0014
34	12.893		48,973	6.003		58,930	2.495		37,596	15.604		49,418	9.113		53,756	3.524		65,187
		0,0102	0,0010		0,0128	0,0013		0,0082	0,0010		0,0103	0,0007		0,0117	0,0012		0,0142	0,0014
40	13.897		48,929	6.467		58,732	2.753		37,548	16.223		49,504	9.953		53,850	3.856		65,217

Exponential Moving Average								
50			100			200		
N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s
	0,0124	0,0011		0,0130	0,0013		0,0078	0,0010
4.309		59,053	2.253		59,216	895		35,575
	0,0120	0,0011		0,0126	0,0013		0,0076	0,0010
8.372		57,307	4.284		57,671	1.956		34,854
	0,0119	0,0011		0,0125	0,0013		0,0075	0,0010
11.787		57,157	6.036		57,505	2.780		34,567
	0,0119	0,0011		0,0125	0,0013		0,0075	0,0010
12.828		57,029	6.435		57,276	3.100		34,511

2% Commission fee- Value Weighted allocation of resource

	Simple Moving Average									Weighted Moving Average								
Size\Days	50			100			200			50			100			200		
	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s
		0,0116	0,0006		0,0136	0,0010		0,0088	0,0842%		0,0117	0,0004		0,0127	0,0009		0,0149	0,0012
10	4.468		56,158	2.087		62,880	831		40,367	6.186		56,658	3.121		59,103	1.191		68,186
		0,0112	0,0006		0,0134	0,0011		0,0085	0,0853%		0,0115	0,0004		0,0122	0,0009		0,0147	0,0012
20	8.530		54,095	4.078		62,042	1.710		39,425	10.873		55,672	5.983		56,768	2.444		68,147
		0,0109	0,0006		0,0132	0,0011		0,0085	0,0858%		0,0114	0,0004		0,0123	0,0009		0,0147	0,0012
34	11.579		52,877	5.739		61,457	2.385		39,347	14.597		55,319	8.638		57,019	3.237		67,938
		0,0110	0,0005		0,0133	0,0011		0,0085	0,0866%		0,0114	0,0004		0,0122	0,0009		0,0147	0,0012
40	12.207		53,313	6.177		61,632	2.690		39,272	15.118		55,228	9.228		56,850	3.489		67,924

Exponential Moving Average								
50			100			200		
N	Stdev	r/s	N	Stdev	r/s	N	Stdev	r/s
	0,0131	0,0008		0,0136	0,0010		0,0081	0,0009
4.155		63,253	2.115		63,044	864		37,108
	0,0128	0,0008		0,0132	0,0010		0,0079	0,0009
8.004		61,721	4.036		61,314	1.934		36,563
	0,0127	0,0008		0,0133	0,0010		0,0078	0,0009
10.947		61,322	5.614		61,527	2.668		36,337
	0,0127	0,0008		0,0132	0,0010		0,0078	0,0009
12.003		61,368	5.969		61,399	3.004		36,240

Buy and Hold

Commission/Days	50	100	200
0%	-0,00213	0,00173	0,00756
1%	-0,00213	0,00173	0,00756
2%	-0,00213	0,00173	0,00756

Appendix 10- Results of Trading Analysis in Dollar Terms

Equal Weigthed Allocation of resource

0% Commission fee

	Equal Weighted Portfolio								
	Simple Moving Average			**Weighted Moving Average**			**Exponential Moving Average**		
Size\Days	50	100	200	50	100	200	50	100	200
10	$8.549.855,60	$9.472.464,29	$4.743.172,33	$8.738.093,11	$9.597.498,53	$9.712.676,43	$11.866.627,05	$8.688.409,57	$5.100.404,44
20	$9.362.122,98	$10.409.634,78	$4.630.631,56	$9.040.243,64	$10.231.236,72	$10.229.249,90	$11.846.870,66	$9.040.851,82	$5.017.186,19
34	$8.508.013,98	$10.508.490,51	$4.860.125,10	$8.367.776,16	$9.672.267,62	$10.389.567,22	$11.039.552,11	$9.243.475,49	$5.033.800,14
40	$8.378.946,83	$10.816.692,40	$4.913.927,41	$8.094.079,32	$9.814.514,48	$10.726.154,44	$11.214.457,72	$9.135.964,59	$5.009.954,46

1% Commission fee

	Equal Weighted Portfolio								
	Simple Moving Average			**Weighted Moving Average**			**Exponential Moving Average**		
Size\Days	50	100	200	50	100	200	50	100	200
10	$4.288.784,93	$6.481.726,68	$3.996.623,19	$3.780.685,46	$5.796.892,89	$6.788.561,48	$6.007.842,58	$5.298.689,62	$4.358.711,62
20	$4.454.920,22	$7.093.702,55	$3.646.395,71	$3.699.943,10	$5.818.369,29	$7.191.213,00	$5.571.406,03	$5.740.814,27	$4.218.789,28
34	$4.003.408,05	$6.744.482,59	$3.796.897,92	$3.015.998,32	$5.983.521,24	$6.774.046,74	$4.956.477,04	$5.568.118,35	$4.07.5380,41
40	$3.954.602,75	$7.065.724,67	$3.881.969,00	$2.975.448,17	$5.615.925,99	$7.016.517,10	$4.895.606,30	$5.809.967,81	$4.131.316,92

2% Commission fee

	Equal Weighted Portfolio								
	Simple Moving Average			**Weighted Moving Average**			**Exponential Moving Average**		
Size\Days	50	100	200	50	100	200	50	100	200
10	$2.457.523,12	$4.270.115,33	$3.271.059,30	$1.899.154,50	$3.613.528,63	$4.772.956,36	$3.222.948,68	$3.746.886,42	$3.597.241,63
20	$2.428.911,34	$4.702.981,58	$3.313.762,97	$1.793.322,70	$3.569.703,21	$4.809.905,03	$2.842.235,76	$3.698.224,40	$3.440.422,65
34	$2.154.778,59	$4.239.687,70	$3.343.509,89	$1.440.667,92	$3.477.283,94	$4.785.897,46	$2.589.363,80	$3.672.524,34	$3.403.644,26
40	$2.006.754,35	$4.550.495,91	$3.287.813,73	$1.437.611,16	$3.298.024,77	$4.808.802,39	$2.495.922,41	$3.638.671,09	$3.473.860,17

Cont. 1 Appendix 10- Results of Trading Analysis in Dollar Terms

Value Weighted Allocation of resources

0% commission fee

	Value Weighted Portfolio								
	Simple Moving Average			**Weighted Moving Average**			**Exponential Moving Average**		
Size\Days	50	100	200	50	100	200	50	100	200
10	$8.931.079,90	$10.666.784,16	$4.918.273,04	$8.271.592,82	$10.316.452,12	$10.584.156,23	$11.312.637,63	$8.860.082,99	$5.166.205,14
20	$8.819.196,85	$11.080.445,19	$4.899.375,67	$8.081.030,37	$10.510.849,50	$11.599.947,05	$11.389.117,85	$9.359.382,44	$5.269.288,13
34	$9.189.523,06	$11.016.842,51	$5.128.346,63	$7.801.694,41	$10.432.499,11	$11.486.570,45	$11.155.605,85	$9.866.290,86	$5.387.033,71
40	$8.979.710,32	$11.247.826,89	$5.164.419,93	$7.855.462,12	$10.459.727,35	$11.831.792,67	$11.352.398,57	$10.088.454,55	$5.395.784,16

1% commission fee

	Value Weighted Portfolio								
	Simple Moving Average			**Weighted Moving Average**			**Exponential Moving Average**		
Size\Days	50	100	200	50	100	200	50	100	200
10	$4.682.709,35	$7.794.567,07	$4.205.476,39	$3.948.093,87	$6.466.080,00	$7.906.716,69	$6.123.011,39	$6.190.835,53	$4.411.234,24
20	$4.851.315,80	$7.877.184,89	$4.155.172,57	$3.609.052,92	$6.637.220,96	$8.491.641,70	$6.158.892,24	$6.358.910,25	$4.493.942,51
34	$4.784.406,39	$7.855.699,37	$4.213.092,52	$3.419.681,84	$6.629.494,48	$8.486.814,00	$5.935.864,32	$6.465.592,61	$4.424.950,60
40	$5.011.449,97	$8.016.928,63	$4.240.465,57	$3.335.599,00	$6.744.911,48	$8.617.298,09	$6.140.313,07	$6.518.058,05	$4.423.305,60

2% Commission fee

	Value Weighted Portfolio								
	Simple Moving Average			**Weighted Moving Average**			**Exponential Moving Average**		
Size\Days	50	100	200	50	100	200	50	100	200
10	$2.593.400,73	$5.241.202,56	$3.555.379,29	$2.025.061,19	$4.433.495,18	$6.289.758,85	$3.461.361,47	$4.169.889,00	$3.715.022,41
20	$2.818.129,48	$5.913.936,97	$3.619.912,25	$1.845.689,57	$4.295.741,47	$6.166.177,94	$3.662.645,25	$4.371.079,55	$3.807.685,65
34	$2.601.543,67	$5.669.082,55	$3.642.705,09	$1.899.311,50	$4.489.686,71	$6.274.593,00	$3.544.636,00	$4.372.234,33	$3.832.537,65
40	$2.466.731,26	$5.690.643,49	$3.689.771,50	$1.848.935,41	$4.311.600,64	$6.274.593,00	$3.555.967,07	$4.434.533,15	$3.858.176,84

Appendix 11- Section 4.10 to Table 6- The Sharpe Ratio

Sharpe Ratio for Equal Weighted Allocation of Resource

Sharpe Ratio 0% Commission fee

	Simple Moving Average			**Weighted Moving Average**			**Exponential Moving Average**		
Size\Days	50	100	200	50	100	200	50	100	200
10	0,1403	0,1108	0,1412	0,1453	0,1213	0,1130	0,1336	0,1291	0,1605
20	0,1591	0,1188	0,1451	0,1574	0,1314	0,1198	0,1391	0,1369	0,1668
34	0,1546	0,1206	0,1528	0,1525	0,1295	0,1211	0,1361	0,1398	0,1696
40	0,1547	0,1222	0,1545	0,1499	0,1302	0,1232	0,1372	0,1400	0,1698

Sharpe Ratio 1% Commission fees

	Simple Moving Average			**Weighted Moving Average**			**Exponential Moving Average**		
Size\Days	50	100	200	50	100	200	50	100	200
10	0,0905	0,0905	0,1230	0,0839	0,0917	0,0937	0,0932	0,0977	0,1428
20	0,1003	0,0976	0,1190	0,0861	0,0968	0,0995	0,0922	0,1059	0,1452
34	0,0948	0,0956	0,1247	0,0737	0,0988	0,0963	0,0864	0,1043	0,1443
40	0,0939	0,0985	0,1277	0,0724	0,0959	0,0986	0,0862	0,1084	0,1463

Sharpe Ratio 2% Commission fees

	Simple Moving Average			**Weighted Moving Average**			**Exponential Moving Average**		
Size\Days	50	100	200	50	100	200	50	100	200
10	0,0526	0,0682	0,1039	0,0376	0,0652	0,0747	0,0572	0,0750	0,1213
20	0,0559	0,0752	0,1082	0,0354	0,0671	0,0771	0,0529	0,0776	0,1215
34	0,0484	0,0701	0,1100	0,0226	0,0661	0,0769	0,0486	0,0777	0,1217
40	0,0441	0,0745	0,1082	0,0225	0,0630	0,0773	0,0467	0,0775	0,1242

Sharpe Ratio for Equal Weighted Allocation of Resource

Sharpe Ratio 0% Commission fee

	Simple Moving Average			**Weighted Moving Average**			**Exponential Moving Average**		
Size\Days	50	100	200	50	100	200	50	100	200
10	0,1255	0,1127	0,1246	0,1257	0,1204	0,1094	0,1224	0,1183	0,1394
20	0,1308	0,1170	0,1284	0,1288	0,1262	0,1156	0,1264	0,1253	0,1447
34	0,1350	0,1178	0,1334	0,1270	0,1267	0,1152	0,1259	0,1292	0,1479
40	0,1334	0,1190	0,1343	0,1278	0,1269	0,1169	0,1271	0,1309	0,1483

Sharpe Ratio 1% Commission fees

	Simple Moving Average			**Weighted Moving Average**			**Exponential Moving Average**		
Size\Days	50	100	200	50	100	200	50	100	200
10	0,0853	0,0961	0,1111	0,0775	0,0941	0,0941	0,0877	0,0970	0,1248
20	0,0919	0,0986	0,1136	0,0743	0,0989	0,0988	0,0908	0,1014	0,1297
34	0,0916	0,0989	0,1153	0,0715	0,0997	0,0985	0,0892	0,1027	0,1296
40	0,0944	0,1002	0,1160	0,0699	0,1004	0,0992	0,0911	0,1035	0,1299

Sharpe Ratio 2% Commission fees

	Simple Moving Average			**Weighted Moving Average**			**Exponential Moving Average**		
Size\Days	50	100	200	50	100	200	50	100	200
10	0,0498	0,0756	0,0960	0,0369	0,0726	0,0817	0,0573	0,0738	0,1080
20	0,0562	0,0823	0,1001	0,0327	0,0741	0,0815	0,0614	0,0784	0,1122
34	0,0531	0,0812	0,1009	0,0344	0,0760	0,0826	0,0603	0,0783	0,1135
40	0,0498	0,0812	0,1022	0,0331	0,0742	0,0831	0,0604	0,0791	0,1144

Appendix 12- Section 4.11 to Bootstrap Analysis

	Bootstrap Result												
Techniques	SMA							WMA					
Days	50							100				100	
Commission (%)	2							1				2	
Resource Allocation*	E	E	E	E	V	V	V	E	V	E	V	E	V
Size	10	20	34	40	10	20	34	10	10	20	20	20	20
r	0,0546%	0,0535%	0,0462%	0,0430%	0,0563%	0,0617%	0,0573%	-0,0555%	0,1144%	0,1078%	0,1167%	0,0775%	0,0913%
s	0,01041	0,00964	0,00968	0,00966	0,01162	0,01121	0,01093	0,00977	0,01222	0,01120	0,01179	0,01178	0,01224
t-statistics	0,65730	1,17190	1,39847**	1,31411**	0,75075	1,06329	1,22575	6,4956***	0,02067	0,04661	-0,00227	2,0014***	1,20988
p-value	0,25460	0,12100	0,08080	0,09510	0,22660	0,14460	0,10930	-0,00049	0,49200	0,48400	0,50000	0,02280	0,11310
n transactions	5235	11014	16121	17258	4.468	8530	11579	3697	3172	7943	6247	7471	5983

Note: *E= Equal Allocation; V=Value Allocation; SMA = Simple Moving Average and WMA=Weighted Moving Average

** significant at 10%
*** significant at 5%